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EFFICIENT LOCALIZATION OF REFUGEES AND MIGRANTS PEOPLE ACROSS TURKEY USING CLUSTERING-BASED DATA TRACKING

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Doctor of Philosophy

Supervisor

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The dissertation titled “EFFICIENT LOCALIZATION OF REFUGEES AND MIGRANTS PEOPLE ACROSS TURKEY USING CLUSTERING-BASED DATA TRACKING” prepared by TALIB MUHSEN ELEBE and submitted on 01-03-2023 has been **accepted unanimously** for the degree of Ph.D in Electrical and Computer Engineering

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I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

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Signature

DEDICATION

In the beginning, I can hardly express my gratitude to "Allah," and I shall always remember his generosity for giving me a hand and a great deal of help to complete this work.

I sincerely thank my great supervisor, Professor Dr. Sefer KURNAZ, for helping me conduct the research and prepare the thesis. Thank you for your help and gaudiness all those years. It was an honor to have you as my supervisor.

This thesis is wholeheartedly dedicated to my beloved family, who have been my source of inspiration and are the reason for my progress and success. I am very grateful to my mother, father, and wife in particular. Thank you for your support all those years.

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ABSTRACT

EFFICIENT DETECTION OF REFUGEES AND MIGRANTS PEOPLE ACROSS TURKEY USING CONVOLUTIONAL NEURAL NETWORK

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In the years following the outbreak of the Syrian Civil War in 2011, non-governmental organizations (NGOs) played a crucial role in assisting refugees and distributing relief to people in need so that they may go about their daily lives without interruption. After years of escalating tensions, several non-governmental organizations (NGOs) in Turkey have shifted their attention to helping the refugee community there. The frequency of natural disasters, armed conflicts, and terrorist attacks has increased during the past 20 years, making family relocation a major issue in many countries. It creates a lot of issues for government agencies and regulatory groups. The goal of this model is to use AI to track refugees in restricted areas. It is challenging to manage refugees' spontaneous movement or encampments since they are susceptible to natural disasters and hostility from humans. To identify and keep track on migrants in restricted areas, a deep learning system based on convolutional neural networks is provided. The suggested approach makes use of Internet of Things (IoT) system to track the whereabouts and activities of refugees in real time. Refugee management might be improved with the use of AI and the Internet of Things. This novel approach makes use of a deep learning model based on a convolutional neural network, which can quickly and reliably identify the face of a displaced individual. To aid authorities in tracking down a specific refugee, the system maintains an open line of communication

with them and often seeks an update on their whereabouts. If a refugee doesn't report where they are, the system will send out a search party to find them. Automatic recognition of non-citizens and their continued tracking has become a breeze with the help of deep learning.
Keywords: Refugee Detection, IoT, Deep Learning, AI, CEP.

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ABBREVIATIONS

ML	:	Machine Learning
Sol	:	Solution
DL	:	Deep Learning
AI	:	Artificial Intelligence
Eq	:	Equation
CEP	:	Coexistence Equilibrium Point
UNHCR	:	UN High Commissioner for Refugees
CNN	:	Convolutional Neural Network
EU	:	European Union
UNFPA	:	United Nations Population Fund
DNN	:	Neural Network
NGO	:	Non-Governmental Organizations
FCNN	:	Fully Convolutional Neural Network
ANN	:	Artificial Neural Network

1. INTRODUCTION

1.1 BACKGROUND

The Syrian civil war has been designated as the world's worst refugee and humanitarian crisis by the United Nations. It has been reported that 3.7% of Turkey's population, or 5.5 million people, are Syrian refugees. Since the conflict in Syria began in 2011, a total of 2, 009, 50 people had sought shelter in Turkey. But the people of Turkey have shown tremendous love and compassion toward the Syrian refugees who have fled to their country. Turkey has built institutional frameworks and several initiatives specifically for the needs of refugees, including expanding its conventional healthcare system to include them. Refugees from Syria and Turks have gotten closer over time. Statistics show that the number of violent occurrences between communities tripled between the middle of 2016 and the middle of 2017 [1]. Half of Turks polled said that tensions between Ankara and Damascus are a major source of division in the country [2]. Therefore, there has been increased academic interest in the topic of refugee integration into Turkish society. Civil society organizations in Turkey have been instrumental in providing relief to and fighting for the protection of Syrian refugees ever since the first wave of migrants entered the country. They have done a lot to help those who had to abandon their houses by providing relief and ensuring they have access to the resources they need to rebuild their life, such as healthcare, employment prospects, and educational chances. The effect of non-governmental organizations (NGOs) on immigrant adaptation has been the subject of a plethora of research [3, 4, 5]. NGOs and other forms of civil society aid refugees, nonetheless, there isn't institutional means to ensure their security. As they travelled, migrants lived in tents, then spread out over the country after arriving, this is what happened: Some of them become citizens and can now legally exit the country. Most refugees, however, do not have any legal means of leaving the nation, making it even more important to establish a mechanism that guarantees their safety. The use of deep learning (DL) and artificial intelligence (AI) methods to verify human emotions, behaviors, and gaze has increased in the past few years [6, 7]. To provide adequate protection, modern businesses need a team of trained security professionals. Unfortunately, security vulnerabilities can occur due to human error. As the speed of globalization is increasing, the ability to rapidly and precisely recognize someone by the way they look has become a critical necessity in current-day society. For the past two decades, face recognition has become a major topic of discussion due to its practical implications in areas such as image analysis and comprehension. The procedure of efficiently detecting a human face using a computer system involves three main steps: photo preprocessing, feature extraction, and recognition classification, as described in the reference [9]. One crucial element entails the examination of the geometric characteristics that contribute to the distinctiveness of each individual's facial structure. Through the process of matching a photographic representation of an individual's facial features with a comprehensive repository of established facial profiles, it becomes feasible to ascertain the specific identify of the person under scrutiny. Nevertheless, it is important to acknowledge that the efficacy of a facial recognition system of this nature may be compromised in the absence of ongoing human supervision. Despite its potential, this technology still encounters challenges in terms of dependability, scalability, and privacy issues. Ideally, an ideal facial recognition system should efficiently and accurately ascertain the identities of individuals.

In the context of Turkey, civil society actors have assumed a crucial function in providing assistance and campaigning for the displaced Syrian populace since the initial influx of refugees into the nation. The contributions made by the individuals in question have played a crucial role in facilitating increased access to vital resources, including sustenance and accommodation, for a larger number of displaced individuals seeking asylum. Furthermore, these initiatives have generated avenues for educational attainment, career prospects, and access to healthcare, so exerting a beneficial influence on the well-being of innumerable displaced individuals. It is noteworthy that in recent times, scholars have commenced investigating the impact of non-governmental organizations (NGOs) on the social cohesiveness of immigrant communities, as evidenced by references [12, 13, and 14]. This study illuminates the wider societal ramifications of the endeavors undertaken by non-governmental organizations (NGOs) in their support and integration of refugee populations.

However, we found that the social capital approach to migrants' social cohesion requires more research. This research aims to answer the question, "Do NGO initiatives on behalf of refugees in Istanbul contribute to community development?" Members of Turkey's civil society have played a crucial role in aiding and advocating for Syria's displaced people ever since the first refugees arrived in the country. They have helped more refugees gain access to necessities like food and shelter, as well as increased opportunities for education, employment, and health care. Only lately [12, 13, and 14] have researchers examined the impact of NGOs on the social cohesion of immigrant communities.

However, we found that the social capital approach to migrants' social cohesion requires more research. This research aims to answer the question, "Do NGO initiatives on behalf of refugees in Istanbul contribute to community development?"

As intermediaries, NGOs can link up those in need with the resources they need to start again and provide for themselves. Finally, social capital refers to the trust and cooperation among a group of individuals that is developed as a result of earlier interactions between those people.

Three holes in our understanding are filled by a new study. To begin, most written work on Syrian refugees has concentrated on three primary areas: safety, cohesion, and respect for human rights. [15].

The preliminary research conducted at the outset of the conflict in Syria, and the subsequent exodus of Syrians focused primarily on their legal status [16] and discussed the critical importance of regulations pertaining to training, employment, and means of sustenance [17]. The consequences of the proposed law on the Syrian citizens' legal standing prompted more discussion [18]. New arguments regarding the future of the Syrian people [19], the value of education for Syrian children, and their needs [20, 21] emerged in the academic literature as a result of the length of the Syrian Civil War. The scant literature on the impact of international nongovernmental organizations (INGOs) on social cohesion in Turkey is in its formative stages and suffers from problems of scale. Others have taken a more global approach, using a variety of locales to examine the greater possibilities and restrictions INGOs have in their involvement with Syrian refugees in Turkey [22], while some studies have concentrated on areas where NGOs working with refugees have worked. The scope of our fieldwork allows us to serve as a link between these two methods.

Several scholars, however, have investigated the lack of a consistent integration policy at length [23]. Previous studies have shown that language is a major hurdle in this setting [24, 25]. Furthermore, there is a long-standing debate among academics as to whether Syrian refugees should be considered when making policy [26, 27, 28, and 29]. After work permits were granted under Temporary Protection in 2017, there was an uptick in published studies on the social harmony about the integration to the Syrian economy as a whole. This research provides new evidence to support these hypotheses. The issuing of Temporary Protection Work Permits in 2017 had a good influence on social cohesion and the integration of Syrian refugees into the Syrian economy, and this impact is substantiated by new evidence presented in this study. This hypothesis implies that the research will most likely produce findings indicating that work licenses have a favorable influence on social harmony and economic integration for Syrian refugees.

Second, there has been a tremendous growth in academic study of Turkish NGOs that work with refugees. The earliest literature on the topic was dominated by reports from non-governmental organizations (NGOs) detailing their work with Syrian refugees in Turkey. Reports by organizations like Mavi Kalem [32] and GAMDER in the year 2013 and the detail the efforts of non-governmental organizations to help Syrians in border cities of Turkey. The importance of NGOs in helping Syrian refugees and the difficulties they encounter were both highlighted in the research. The author distinguished between religious and human rights groups and their activity in a more in-depth analysis of NGOs' capacities and functions [33]. The study's author [4] not only proposed a new category for nongovernmental organizations (NGOs) in Turkey working on refugee and migrant issues, but also showed how philosophical and religious beliefs have affected the formation and sustainability of some NGOs. This research addresses a gap in existing literature.

A large body of research from countries as diverse as Sweden, Germany, the Netherlands, Myanmar, and Turkey shows how challenging it is for civil society to foster social cohesion and integration due to poor policies and practices. This study makes a significant addition to the current literature by examining the initiatives taken by local, national, and international nongovernmental organizations (NGOs) as well as NGOs run by refugees in Turkey to strengthen bonds of friendship and cooperation between the two countries' populations.

Academic interest in Turkey's civil society has increased dramatically since the turn of the millennium. Some of these studies (such as [37]) have taken a more global view, while others (such as [34], [35], [36], and [4]) have focused on specific topics including women, the environment, foreign money, and refugees in Turkey. Other scholars have also studied the emergence of new types of civic organization in the wake of the 2013 Gezi Protests (e.g. [38]). This article adds to current corpus of knowledge by focusing on the work of non-governmental organizations (NGOs) across the world and refugee-led organizations in Turkey.

In the context of NGO projects, we drew on qualitative information gleaned from the field. Between August 2019 and September 2020, we interviewed twelve Istanbul-based organizations' spokespeople in-depth, semi-structured interviews (see Annex 1). Given that Istanbul is home to the bulk of Turkey's Syrian refugee population, we opted to conduct our research there.. Keep in mind that many Syrian migrants chose Istanbul as their new home when calculating the importance of social capital. During the interviews, we probed their experiences working with refugees. In particular, we looked at the backgrounds of everyone involved, how they chose which refugees to help, how those groups interacted with one another, the problems that arose, and the suggestions that were offered to fix them. Each conversation lasted for around an hour and could have been conducted in either Turkish or English. We spoke with representatives from non-governmental organizations (NGOs) concerned not only with refugees or refugee-related challenges but also with psychological wellness, environment, corporate affairs, and humanitarian assistance to assess whether the activities established or reinforced a range of relations and examine the effects for social cohesiveness. To round out our research, we also interviewed representatives of local and international non-governmental organizations (NGOs) (including community-based Turkish and Syrian organizations). We adopted the purposive and snowball selection processes since there is no central registry of organizations that provide aid to migrants. To supplement our primary investigation, we looked at the websites and publications of additional non-governmental groups. The thematic content analysis applied to the data focused mostly on social capital. This research was sanctioned by the University of Liverpool's advisory board on human experimentation. Each participant was given a packet of information that explained the purpose of the study, how it would be conducted, and any ethical considerations that had to be taken into account. If they sign the permission form, that shows they understand the terms and agree to the confidentiality of their information. They were also made aware that taking part in the study was purely voluntary.

1.2 SYRIAN REFUGEES IN TURKEY

As fighting escalated in Syria's civil war, tens of thousands of people sought safety in Turkey. As a result of this policy, Turkey currently accepts more refugees than any other country. As of the most recent count in 2021, the UNHCR estimated that there were 330,000 asylum applicants from various nationalities in Turkey, in addition to the 3.6 million Syrians already there. Interesting too is the fact that temporary housing accounts a home for just 2% of Syrian refugees leaving 98% distributed over Turkey. There is evidence that the majority of these migrants live in Istanbul, Istanbul, Izmir, and Bursa as well as in the southeasterly cities of Gaziantep, Urfa, and Hatay. With 524,497 Syrian refugees now residing there, Istanbul has the largest refugee population in all of Turkey. According to Figure 1.1, Turkey has 3,650,496 Syrian refugees registered there, making it the largest host nation in the region and the globe for this group. Around 90% of Syrian refugees, in late 2015, the United Nations Secretary-General's Office for Refugees (UNHCR) projected that 65.6 million Syrians, notwithstanding the conservative estimate of the Turkish government that only 59,645 Syrians were being sheltered in camps, would be living outside of camps by 2020. During the time period under review, the vast majority of Syrians in Turkey were not living in designated "camps" but rather with local families. Because of its central location in the Middle East, Turkey serves as a hub for migrants from all across the region. There is a dearth of information about the number of refugees and asylum seekers that Turkey welcomed in September of 2020, but the United Nations High Commissioner for Refugees (UNHCR) estimates that number to be in excess of 330,000. The majority of these individuals were evacuees from Afghanistan, Iraq, and Iran.

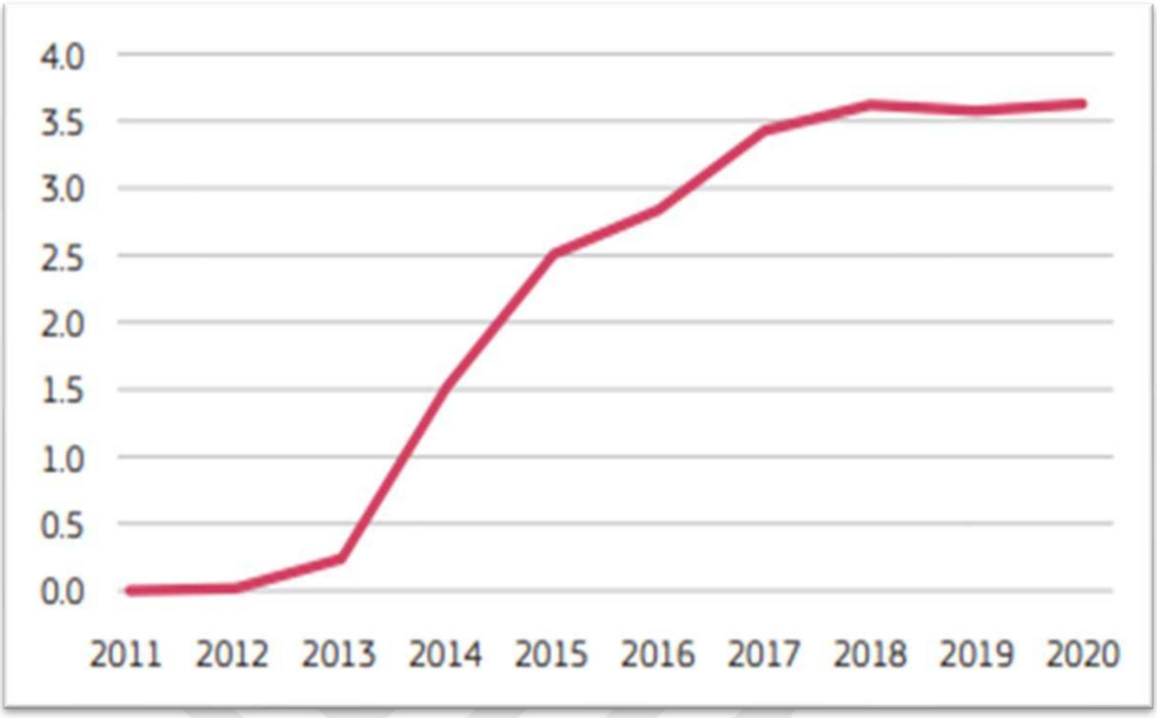


Figure 1.1: From 2011 Until 2020, Total Syrian Refugees Registered in Turkey (Millions).

Despite having signed both the 1951 Refugee Convention and the 1967 Protocol, Turkey continues to limit refugees based on where in the world they are from. As a result, Turkey is not a safe haven for anyone seeking refuge from persecution in nations outside of Europe.

Furthermore, the "The steps and Principles" concerning Opportunities Transportation and Aliens Upon their arrival in Turkey as Everyone or in Communities Wishing to File for Protection either from the nation of Turkey or asking for Housing Permit to Seek Refugees from Yet another Country" Enforcement of 1994 was for many years the sole document regarding the movement of migrants in Turkey due to the lack of national rules on protection abroad. During the course of the Syrian Civil War, however, the residents of Syria were exempt from the 1994 Regulation. Legal protection for Syrian citizens remained murky from 2011 until 2014 [28], when the Education and Health Ministries issued extra laws within their purviews to help and cater to the varied requirements of Syrian people. A positive response was shown with the passage of Law No. 6458 on Foreigners and International Protection (henceforth referred to as LFIP) in April of 2014. Emergency safeguards in the case of a "mass inflow crisis" are outlined in Article 91 of the LFIP. As a follow-up to the LFIP and to provide clarity for requests made under Article 91, the governing bodies enacted the "Temporary Protection Regulation" in September of 2014. Syrian nationals, IDPs, and refugees uprooted as a result of the events of April 28, 2011, were only granted temporary protection under this law. To clarify the significance of the many laws pertaining to refugees in areas including healthcare, higher education, and work permits, several ministries have developed supplementary regulations and administrative directives.

Due to their temporary protected status, Refugees from Syria in Turkey have access to public services such as healthcare, education, and the labor market. While the term "integration" is used, the LFIP also makes use of the notion of "harmonization" to increase the likelihood that the refugees will be accepted by Turkish society. An official National Harmonization Strategy and Action Plan was passed in Turkey in 2018 with the goal of fostering mutual harmony between people receiving short-term international security and the native community.

The European Union (EU) provided six billion euros to help Turkey provide for the needs of refugees in 2015 and 2016, when it also issued Plan of Action and European Union-Turkey Relations Declaration. Increased refugee access to healthcare, education, and employment are all targets of EU-funded initiatives (European Commission, 2020). However, policy uncertainty immediately emerged, causing problems for the assimilation of Syrian refugees. Syrians suffer obstacles in exercising their obstacles, including registration and language issues (low levels of Turkish proficiency), make it difficult for people to exercise their rights to a safe and healthy environment, medical treatment, and an appropriate education. According to studies [39], it takes more than meeting the fundamental requirements of both groups (such as the acquisition of a shared language, access to healthcare, education, and gainful employment) to achieve successful integration. Economic opportunity, social networks, and a feeling of safety were found to be the most alluring aspects of Istanbul for Syrian refugees by the Istanbul Metropolitan Municipality.

Refugee and migrant issues are receiving a lot of attention from NGOs and international NGOs in Turkey, in particular where there are the most Syrian refugees. When it came to providing refugees with necessities like registration, advocacy and repatriation, linguistic and educational study, employment, and livelihood, and so on, non-governmental organizations (NGOs) played a pivotal role. [3].

Humanitarian aid operations for refugees fleeing the Syrian civil war were mostly carried out in 2011 by NGOs and foreign NGOs in conjunction together with the AFAD Presidency of Emergency and Disaster Management. Therefore, the Turkish government adopted the

Provisional Protection Law in 2014 to protect Syrian refugees, adopting an open-door policy. from deportation., and provision of basic requirements. Therefore, it is safe to assume that any NGO projects initiated in Turkey after 2014 adhered to the requirements of the country's Temporary Protection Law. Over time, though, their efforts expanded to include things like social inclusion, job creation, and classroom instruction. Since 2015, non-governmental organizations have prioritized the promotion of social cohesion by doing projects that back up government initiatives. Particularly in the realm of education, the government has made it easier for Syrians to enroll in courses, and non-profits have created anti-bias training for professors and students. Jobs for Syrian refugees have increased significantly when NGOs began providing them with professional training in addition to teaching them the basics. The EU's Fund for Refugees in Turkey is one example of the foreign financing that has been channeled through the NGOs to assist with the refugee situation [40].

NGOs in Turkey have shifted their focus from crisis aid to strengthening the social fabric of refugee camps and the government's welfare system since the Syrian Civil War's conclusion. Non-governmental organizations (NGOs) provide crucial services and facilitate relationships between the host and refugee populations, according to one study [5].

1.3 MIGRATION CRISIS IN SYRIAN: A BACKGROUND

One of the worst tragedies in human history is unfolding with the fate of Syrian refugees. Millions of Syrians and their relatives have fled to neighboring countries like Turkey since the crisis broke out in the same year. The refugee crisis has exacerbated a challenging scenario for the countries that are taking in the displaced people. We want to put the situation of Syrian refugees in Turkey into perspective in this article.

In March 2011, what started as peaceful protests against President Bashar al-Assad quickly became violent. An all-out civil war has broken out as a result of the disagreement, with several factions vying for control. The fighting has displaced millions of people, many of whom have fled to neighboring countries in search of safety. Since around 3.6 million Syrians have migrated to Turkey, it has become one of the world's most populated nations.

There have been significant social and economic effects of the entry of Syrian refugees into Turkey. Many of the world's refugees, who are presently living in congested camps or informal settlements, have fallen on Turkey's shoulders. The burden on the country's infrastructure, healthcare system, and social services due to the inflow of migrants has been substantial. The enormous number of migrants has harmed the economy in several ways, including the high unemployment rates.

Despite these setbacks, Turkey has made important contributions to the international response to the plight of displaced Syrians. The government has tried to integrate refugees into society by providing them with social amenities like healthcare and education. However, there have been reports of abuse and mistreatment of migrants in Turkey. Some refugees have even said they have experienced intolerance and discrimination.

There are wider geopolitical ramifications of the Syrian refugee crisis beyond the difficulties refugees themselves are experiencing. Many countries have taken sides in the fight and lent their assistance to various groups, creating instability across the area. Extremist groups like ISIS, which have caused destruction on a global scale, have also emerged because of the conflict.

Overall, the Syrian migration crisis has had a major effect on the international geopolitical environment and on the refugees in Turkey. Since the issue is so intricate, there is no easy solution. Nonetheless, the international community must keep helping refugees and host countries while looking for a peaceful resolution to the Syrian war.

1.4 RIGHT OF REFUGEES TO HEALTH UNDER TURKISH LAW

Present global legislation does not guarantee access to healthcare for migrants, refugees, or asylum seekers, and this issue is the subject of continuous discussion. Several international Methods and Conventions, such as the Convention of Geneva and its Further Protocols, the 1969 Organization of African Unity Refugee Protocol in Africa, the 1984 Declaration of Cartagena in Latin America, and the European Union's Charter of Basic Rights, imply a hidden international consensus on the social rights of refugees. Anyone "in the same circumstances" as a refugee is afforded the same protections under the law.

The right to form and join associations, to work for oneself or for another, to pursue a career in the liberal arts, to obtain low-cost housing and public education, to move about freely and freely acquire property, are all included in this category. Regrettably not covered are safeguards for health and the social factors that influence medical care. No social rights, like as medical treatment or other economic benefits, are guaranteed to migrants or asylum seekers. The right to medical care is guaranteed under the Constitution of Turkey. The legislation governing refuge seekers is very similar to EU and UN norms.

Therefore, under the 1967 Protocol and the Geneva Convention of 1951, refugees are entitled to some social protections.

Turkey will only take in Europeans as refugees because of the geographical restrictions imposed by the Geneva Convention. This implies that refugees from countries outside of Europe are not covered by Turkey's responsibilities under the Convention. The Turkish government is already considering new sui generis legal groups that would help Syrian refugees. Under the Law on Foreigners and International Protection, refugees from countries outside of Europe receive "conditional refugee" status, whereas refugees from Syria are granted temporary protection. The Turkish Ministry of Biomedical published a "Circular on Health Facilities for the Residents under Transitional Protection" that ensured these Syrian refugees' access to medical treatment. However, these rules do not have clear definitions and do not adhere to international norms [8, 19].

In November 2014, Syrian refugees made up 2.1% of Turkey's population, according to official data. As of September 2015, this figure had risen to 2.5 percent. The influx of Syrian refugees has added an estimated 1.2 million people to the population of border cities in Turkey, bringing the overall number of Turks to 10 million [41].

Health and the social elements that affect health have suffered as a result of the unpredictable and fast population expansion.

Ten border cities in Turkey host refugee camps. In 2014, 42,241 people called one of these 21 camps in these cities their home. Primary medical treatment is provided through community health centers, whereas secondary care is provided by hospitals and polyclinics. Immunizations, newborn and child monitoring, prenatal care, family planning, and mental health counseling are all examples of essential medical care.

Primary and secondary medical services are freely available to the Syrian refugees residing in the camps. Those in need of more extensive treatment are taken to publicly financed hospitals at no further expense to the patient. When they leave the camps, refugees can receive primary and secondary treatment at no cost.

When need for healthcare is exceeding the capacity of healthcare providers in the regions. In 2015, state hospitals provided care for over 500,000 Syrian refugees living in camps. More than 35,000 Syrian women are thought to have given birth in Turkey in 2016, according to estimates from the Ministry of Health. Between 30 and 40 percent of hospital beds in border provinces of Syria are occupied by Syrian refugees. In addition to the obvious issue of crowding, locals have also voiced their frustration that Syrians are taking use of medical services without providing the "real" right holders (the Turkish people) with equal access.

Refugee health centers were set up to help with this burden. Primary care is provided to Syrian refugees by these clinics, which work in conjunction with local community health centers. Fifty health centers are currently available to refugees in 13 cities across Turkey. To better fulfill the unique requirements of refugees, refugee health clinics often hire specialists from a wide range of fields in addition to traditional medical staff.

There is also a greater presence of medical workers in border cities with Syria. The number of physicians in Gaziantep, where many Syrian refugees have lived, rose from 156 to 380 and from 65 to 179 between 2015 and 2016. It is imperative that funds be allocated to reproductive health care. Free copper and vitamin D supplements are available to refugee women who are pregnant or breastfeeding.

Community health centers typically offer free contraception services and counseling on sexual and reproductive health. Brochures in Arabic are translated and distributed to refugees by the UNFPA to educate them on topics such as birth control, nutrition, and sexually transmitted diseases. Community health facilities also offer screenings for newborns of Syrian refugees. In 2014, about 40,000 infants were screened for congenital disorders such hypothyroidism, phenylketonuria, and hearing loss. Vitamin D and iron are two examples of the micronutrient supplements given to newborns.

1.5 CHALLENGES FACED BY SYRIAN REFUGEES IN TURKEY

Turkey, which currently hosts the greatest number of Syrian migrants globally, has been profoundly impacted by the refugee crisis. In 2021, approximately 3.7 million Syrians will have officially registered as refugees in Turkey.

The lack of access to education and employment opportunities is a major problem for Syrian refugees in Turkey. Despite being in Turkey, just 36% of Syrian refugee children were registered in school during the 2019-2020 school year, according to a UNHCR evaluation.

As a result of widespread discrimination in the workplace, Syrian refugees are often forced to labor for low wages on the black market.

Living circumstances for Syrian refugees in Turkey are a serious issue. Many refugees and immigrants from Syria are forced to live in unsanitary informal settlements and overcrowded shared apartments. People outside of refugee camps face a severe lack of basic services, including water, sanitation, and medical treatment.

Syrian refugees in Turkey have a major challenge due to the linguistic barrier. Despite some shared linguistic features, many Syrian refugees in Turkey have a hard time communicating with native Turkish speakers, making it difficult for them to access services, find work, and integrate into Turkish society.

Many Syrians who have fled to Turkey have had a hard time adjusting to life there. Many Syrian refugees still experience social stigma, discrimination, and hostility from Turkish citizens, despite attempts by the Turkish government and organizations of civil society to assist them assimilate. This may lead to less chances for people to meet one other and engage with their neighbors.

Syrian refugees in Turkish also face difficulties accessing adequate medical treatment. Despite the availability of public healthcare in Turkey, it can be difficult for Syrian refugees to access care there owing to language barriers, a lack of knowing, and administrative hoops. In addition, many Syrian refugees may have unique medical needs connected to the Syrian conflict that the present medical system in the nation is ill-equipped to address, such as mental health issues and wounds sustained as a consequence of violent warfare.

Last but not least, many Syrian refugees in Turkey confront difficult bureaucratic processes when trying to collect social assistance, gain legal status, and other similar tasks. Refugees' already precarious position may be weakened further because of these obstructions.

One of the most pressing issues for Syrian migrants in Turkey is the dearth of available jobs. Refugees may have trouble finding work in Turkey because of the language barrier and the need for a formal education. To survive, many refugees are compelled to take on exploitative, low-paying employment or engage in illegal activities. Refugees are seen as competition for jobs by many Turks, which only makes the situation worse.

Achieving Success in School: Refugees from Syria in Turkey also have additional concerns, including a lack of educational opportunities. Language barriers, a lack of school materials, and budgetary constraints prevent many refugee children from attending school. When kids are troubled and stressed out, they have a harder time adjusting to school and making friends.

Xenophobia and bigotry are pervasive problems in Turkey, especially for Syrian refugees living there. Verbal and physical assaults, as well as being shut out of social and professional circles, are all possible outcomes of prejudice against Syrians.

Many Syrian refugees in Turkey are residing in overcrowded, substandard housing. This could exacerbate relations between the refugees and their Turkish neighbors and cause health and safety issues.

Refugees from Syria in Turkey often have difficulty gaining access to medical care, especially those living in rural areas. This is so because of problems with prejudice and language hurdles, as well as a deficiency in healthcare facilities and resources. Many refugees either go without medical care or are treated by unofficial practitioners.

Syrian refugees in Turkey have endured tremendous suffering because of their forced relocation, which can exacerbate preexisting disorders of the mind include gloom and worry and the scars left by traumatic experiences (PTSD). Unfortunately, access to mental health care is difficult for migrants in Turkey because there are so few institutions, and they tend to carry a stigma.

Many people are unable to receive life-saving medical attention because of linguistic barriers. Although Turkey has tried to hire interpreters to help with this problem, not enough are available to meet demand. A major challenge for Turkish medical professionals is the influx of Syrian refugees. Since Syrian refugees frequently shift from one place to another, it is difficult for pregnant women, new moms, and patients with chronic diseases can all benefit from the close monitoring that is provided by community health care centers [42].

To get public benefits like healthcare, Syrian refugees must first register with the government. Syrian migrants have been systematically registering at camps ever since the flooding began. Those who opted to reside outside of concentration camps, however, do not have this luxury.

Many government agencies have to re-register since the country's data system is so outdated and badly managed. Apprehension about being kicked out of the country prevents some refugees from registering formally. Because of this, some legitimate refugees avoid registering. It is unknown how many Syrians have sought sanctuary in Turkey due to problems with the registration process. Because of GDMM's advancement, a centralized database including information on all refugees has been built and is currently available online. Registration using this online site is required before Syrian refugees may get government benefits including healthcare. This strategy not only improved data quality but also facilitated the formal registration of Syrian refugees [42].

Finally, Syrian refugees in Turkey confront numerous challenges, including discrimination, poor living circumstances, a lack of resources, and limited educational opportunities. There needs to be a concerted and all-encompassing effort from the Turkish government and the international community to solve these problems. This plan should include actions to combat discrimination and further social integration, as well as enhanced support for job, healthcare, and educational possibilities. Syrian refugees in Turkey encounter numerous obstacles related to education, employment, housing, language hurdles, social integration, healthcare, and legal status. To solve these problems, we need an all-encompassing plan that gives top priority to protecting and including refugees, encourages their integration into host communities, and tackles the structural and systemic causes of displacement and forced migration.

1.6 MOTIVAION

The current refugee situation has worsened to the point where it is one of the world's most significant humanitarian tragedies. The rising number of refugees, especially those escaping war-torn countries like Syria, highlights the critical need for the development of efficient and effective systems for identifying and tracking these individuals. It is difficult to find and follow down migrants from Syria because Turkey is one of the primary destinations for Syrian refugees.

Manually identifying and registering people as refugees is a time-consuming and inefficient technique for identifying them. Moreover, using these approaches to keep tabs on refugees after they have been recognized does not give trustworthy results because it is impossible to precisely identify refugees. Innovative and efficient solutions are needed to meet these difficulties head-on.

The requirement for an effective, trustworthy, and reasonably priced method of tracking and identifying refugees in public settings drove the creation of the suggested hybrid deep learning-based technology. To get beyond the limitations of conventional approaches, we will compile a database of photos taken of refugees as they enter Turkey. The database serves as a dataset for a CNN to learn from (CNN) model that can recognize and identify refugees in several monitoring zones in real time.

The proposed approach was motivated by the need to keep constant monitor and track of refugees. The technology uses the tracking and monitoring function to keep refugees safe and to always know where they are. Refugees are kept in the loop and monitored on a regular basis. If a refugee doesn't react to the system within two days, it will try to call their mobile phone number to obtain a current location report. If more than 10 days have passed since the last contact with a refugee, the system will trigger an alarm to send out search parties.

One of the main goals of this plan is to put into action an effective method of monitoring and identifying refugees as they move about in open areas. The system was developed to address the shortcomings of existing approaches to migration detection. The time and money required to manually register and identify refugees is just one of these challenges. The policy also considers the necessity of constant surveillance of refugees to guarantee their security and well-being.

The major focus of this line of research is to develop a cutting-edge method for tracking the whereabouts of refugees in public. The developed hybrid deep learning technique provides an economical and trustworthy answer, allowing for the continuous tracking of displaced people in real time. Some of the difficulties that refugees face in Turkey and elsewhere can be mitigated by employing this technology to track their whereabouts and secure their safety.

1.7 RESEARCH QUESTIONS

The purpose of the proposed research is to find solutions to problems experienced by refugees and immigrants in community settings. It is being looked at how a hybrid deep learning approach might be utilized to monitor incoming migrants and assure their safety in crowded areas.

The research suggests using a deep learning framework, specifically a CNN model, to spot and locate refugee faces in otherwise unintelligible CCTV data. To identify refugees in real time across numerous monitoring locations, the system would first create a database of photos of migrants arriving in Turkey, and then use the CNN model it had been trained on to do so. The refugees will be linked with and tracked by technology on a regular basis to ensure their safety.

The most important takeaway from the research is the need for constant surveillance of refugee movements to ensure their security. After two days, the system would randomly contact the migrants via their smartphones to check on their whereabouts. If the refugee does not report their whereabouts within ten days, the system will dispatch a search party to locate them. If a person leaves the nation without proper documentation or disappears, the system will immediately notify security.

This research subject seeks to answer the questions of (a) how well the suggested hybrid strategy protects migrants in public settings, and (b) how well it uses deep learning techniques to detect and locate migrants in real time. Examining how quickly authorities are notified of issues like illegal immigration and missing people is another goal of the study.

Important areas of study include the following:

a. How reliable is a hybrid technique that makes use of deep learning to identify refugees?

b. Can faces of refugees be reliably identified and located in low-quality, high-noise CCTV images using deep learning architecture?

c. How concerned about their privacy are refugees, and how open are they to having this technology used to ensure their safety?

d. If Turkey adopts this policy, how will it affect the country's ability to manage its refugee population and maintain public safety?

e. How could this method be enhanced so that it can be used in other countries or regions with high refugee populations?

1.8 CONTRIBUTIONS

The authors of this work suggest a deep learning-based hybrid strategy for recognizing migrants in public spaces as a means of overcoming these obstacles. The software compiles a photo archive of refugees entering Turkey. To detect refugees in real time, a CNN model is trained on an image database and then deployed to several types of monitoring. Refugees can be tracked by the system because of the constant communication with them. After two days, the system will randomly contact the refugees via their smartphones to inquire as to their whereabouts. If a refugee hasn't checked in with their whereabouts in ten days, the system will send out a search team to locate them. Here we briefly highlight the study's key insights and contributions:

a. Recognize and localize refugee faces in high-noise, low-transparency CCTV photos using a deep learning system.
b. Protect the refugees by keeping tabs on their whereabouts at all times.

Anyone you suspect of having left the country improperly or is missing must be reported to authorities immediately.

This research presented a significant system that uses deep learning models for imagine classification and recognition.

This system uses state-of-the-art deep learning models, such as VGG16 and Inception V3, which have been shown to achieve very high rates of accuracy and precision. In medical imaging, security, and autonomous cars, for example, precise classification and recognition are essential, so this is of paramount importance.

The system uses these deep learning models, which leads to higher F1-Scores and better recall. For jobs like disease diagnosis and anomaly identification, this implies it not only correctly detects positive cases but also reduces the number of false negatives.

Using deep learning models embedded in security cameras to do real-time face recognition and identification improves safety protocols. It is extremely useful for law enforcement and public safety since it may immediately identify people of interest, possible threats, or missing persons.

Deep learning models can be used to automate complicated activities, making them more efficient and eliminating the need for human interaction. This can help save time and effort across the board, from data analysis to quality assurance to content moderation.

Deep learning models are scalable, meaning they may be applied to increasingly vast datasets and more difficult tasks. The system's scalability means it can handle ever-increasing data loads, making it useful for tasks like content analysis on social media and financial fraud detection.

Because of their malleability, these models can be tailored to serve a variety of purposes. They are adaptable because they can be taught to identify a wide range of items, patterns, and outliers. As deep learning models develop, their effectiveness can be steadily enhanced.

Research and development built on this framework have the ability to address more difficult problems and fuel technological progress.
While there may be some up-front costs associated with developing deep learning models, these investments typically pay for themselves in the form of increased productivity, accuracy, and efficiency across an organization.
In conclusion, the presented system is significant because it may deliver precise, efficient, and automated answers to problems in fields as diverse as security, healthcare, industrial automation, and more. Because of its flexibility and adaptability, it can be used in a wide range of contexts, making significant contributions to the development of new technologies and the enhancement of existing ones.

1.9 RESEARCH HYPOTHESIS

Based on the approach described, the research hypothesis is as follow:
"Hypothesis: Using artificial intelligence (AI) and the Internet of Things (IoT) in refugee management, especially for tracking and identifying refugees in restricted areas result in a more efficient and effective system for monitoring and assisting refugees in Turkey." This new approach, which incorporates deep learning and convolutional neural networks improve refugee management in the face of natural catastrophes, conflicts, and other problems."
This hypothesis implies that the research attempts to demonstrate the efficacy of the suggested AI and IoT-based system in refugee management, particularly in Turkey, where refugees encounter a variety of obstacles. According to the theory, modern technology and deep learning models will improve refugee tracking and identification.

1.10 RESEARCH STRUCTURE

The next steps for this study are outlined in the following table. In the last chapter, we discussed the results of a wide variety of previous research on the issues of refugee safety, security, and healthcare. In Chapter III, we discuss the technique used in the study. In Chapter IV, we present the empirical findings of our deep learning model. In Chapter V, we discuss the many caveats of our investigation. The report concludes with a chapter that summarizes its findings and makes some suggestions for moving forward.

2. LITERATURE REVIEW

2.1 BACKGROUND

More than 3.6 million Syrians have made Turkey their home, joining the nearly 400,000 asylum-seekers and refugees from other countries. UN Human Rights reporting can be found at reporting.unhcr.org. Immigrants from Azerbaijan, Bulgaria, Germany, and Iraq make up a sizable portion of Turkey's total migrant population. It's likely that tensions between the EU and Turkey will remain high because of the refugee situation. Turkey would certainly continue to use the "refugee card" as a bargaining chip against Europe for some time. Numerous innocent lives have become a negotiating chip [43]; nonetheless, the refugee problem must be considered apart from the admissions program if this major humanitarian tragedy is to be averted.

The refugee issue has been exacerbated in large part due to the flow of Syrians into Turkey, which has been driven by the conflict in Syria and the military action of other a dominant position against Syria. Turkey's role in the current financial deadlock can't be ignored.

By looking at how other countries with a similar approach fare, we can gauge how receptive the Turkish healthcare system is to change.

	Turkey	New Zeland	Germany	Canada
Total Refugees	6.1 million	1.1 million	13.1 million	8 million
Physician/10.000 population	17.5	35.9	42.5	23.1
Nurses and midwives/10.000 population	27.11	124.5	132.4	98.8

Figure 2.1: Comparison with Other Countries.

Many publications [44-47] discussed the political and social effects of the influx of refugees into Europe in 2015 and 2016. Particularly relevant to this research are accounts of the daily lives of refugees on the journey to Europe.

Many people who traveled the Balkan route said that their smartphones were vital since they allowed them to stay in touch with loved ones while on the road [48]. They find others to help them on their voyage, including smugglers, through social media and online chat. They may find important places along the way, gather and hand out necessary paperwork, and more.

Communication via social media is rapidly becoming the norm. Facebook, Twitter, Instagram, and Google Plus are the top four social media platforms among migrants [49]. However, migrants are hesitant to use social media out of fear that authorities such as police or coast guards may be monitoring their activity. Because of this, they occasionally resort to using secret online spaces [50]. Problems with smartphones and internet access are two examples of the kinds of logistical barriers that could prevent people from fully embracing social media.

Many migrants rely on social media while on the move, therefore this data can be used for insightful study and analysis of the plight of refugees.

Specific instances from Flickr and Twitter examined by Curry et al. show the potential of internet-based data for retrieving information on refugee travels [51]. Authorities and humanitarian organizations frequently use social media data that incorporates geographic and sociological data on refugee flows.

However, there are still many open questions about the proper way to utilize social media data, such as how to account for potential biases, the quality of the data, and the best approach to analyzing it. To better understand migration patterns during the 2015 refugee crisis, Hübl et al. [52] looked at geotagged tweets. They tallied up the paths taken by refugees to spot circulation patterns. Due to a dearth of information, they were only able to propose a handful of possible refugee escape routes. Using route-based theme groups, they also found areas where Twitter users frequently discuss refugees. While they did uncover certain refugee-related trends that might be determined, they also found that additional location data could be derived from the tweets' language, which could reinforce the research conclusions. Petutschnig et al. investigated ways to improve access to data for refugees on the move. Doing a geographical study using geo-social media data [53].

They tried out a few different approaches on the geo-social media dataset's semantic, geographical, and temporal dimensions, and proved that analysis of all three dimensions together yields the best results. By conducting a thorough investigation of the posts, they will be able to learn more about the subject matter and widen the scope of their study. Additionally, they should have analyzed more data sets.

Machine learning algorithms may be able to extract useful information about refugees from unstructured language if they are trained on annotated data. The powerful and novel idea of "word embeddings" allows for the incorporation of context to preserve semantic similarity across words. This method provides more flexibility than the conventional pipeline, which entails pre-processing steps such as stemming, lemmatization, among other things, before using n-grams to construct BoW bags of words. While BoW models don't take inter-work interactions into account, time-series data approaches like recurrent neuronal networks in addition to short-term neural networks do. Recent research by Bai et al. [54] shows that in some sequence modeling applications, a CNN performs better than other methods. Importantly, we need to think about a mix of CNNs working on word-level embedding, as has been done effectively for sentiment recognition, question categorization, and subject categorization [55-58].

2.2 SYRIAN REFUGEES IN TURKEY

Turkey welcomed Syrian refugees as soon as the civil war broke out. Because of this policy, Turkey is currently taking in the most refugees of any country. Recent UNHCR about 3.6 million Syrians are among the estimated 330,000 asylum seekers in Turkey. Only 2% of Syrian refugees in Turkey live in official refugee camps; the remaining 98% are dispersed around the country. There is evidence that most of these migrants live in urban centers in Turkey's southeast, including Urfa and Hatay, as well as the cities of Istanbul, Izmir, Bursa, and Gaziantep. Turkey's DG of Migration Management estimates that as of 2021 there were 524,497 Syrian refugees residing in Istanbul. [59] This makes Istanbul the city where there are the most people who have fled their country.

Although it has signed both the 1951 Refugee Convention and the 1967 Protocol, Turkey must lift its geographical restrictions on migrants. Thus, anyone escaping persecution in countries other than Europe cannot seek asylum in Turkey.

The 1994 Regulation was established as a result of a legislative void in Turkey and was a crucial document that carefully outlined the "The steps and Fundamentals related to Potential Population Movements and Aliens Coming in Turkey as either Those or in Communities Wishing to Request Asylum Either to Turkey or Looking for Residence Permission is required in order to Find Asylum from Another Country." This law was established as the basic framework for the administration of international protection in Turkey.

In essence, this regulation served as the main guideline for handling a range of complicated issues involving people and groups who arrived in Turkey with the intention of seeking asylum either inside Turkish borders or by obtaining residence permits in order to seek asylum from other countries. It was especially significant since it covered a wide range of topics, including immigration, international protection, and asylum-seeking efforts.

In the perspective of global protection, the 1994 Regulation was crucial. With the establishment of a planned and orderly system for managing the influx of people in need of asylum or residence permits for seeking asylum abroad, it outlined the particular steps to be taken. It sought to guarantee both the rights of persons seeking protection and the regulatory integrity of the procedure by providing clear instructions.

The law set forth the legal framework and administrative procedures that Turkish authorities must follow when interacting with migrants and asylum seekers. It provided information on the requirements for awarding asylum and a permit to remain in the country. The legislation also emphasized the duties of pertinent institutions and agencies engaged in the procedure.

The 1994 Regulation has changed throughout time in response to altering circumstances and advancements in international law, indicating Turkey's dedication to maintaining humanitarian ideals and obligations with regard to asylum. It demonstrated Turkey's commitment to offering international protection to individuals in need while upholding a smooth and legal procedure.

During the Syrian Civil War, however, Syrian citizens were not covered by the 1994 Regulation. Therefore, the legal status of Syrian nationals was unclear from 2011 to 2014 [60]. The Education and Health Ministries, acting within their purviews, enacted supplementary laws to help Syrian nationals and cater to their specific requirements. On April 1, 2014, in an effort to solve this issue, the government enacted LFIP, or The International Protection and Third-Country Nationals Act (Law No. 6458). Provisional safety measures in the case of a "mass inflow situation" are outlined in Section 91 of the LFIP. As a sequel to the LFIP and in order to specify the scope of application of Article 91, the government approved the "Temporary Safety Regulation" in September of 2014. The only people who were granted temporary protection because of the events of April 28 were Syrian nationals, stateless people, and Syrian refugees. This happened because of what happened on April 28, 2011. Several ministries have released a wide range of supplementary laws and regulatory orders to explain the execution of regulations pertaining to the medical care, higher education, and employment authorization of refugees.

The Syrian refugees residing in Turkey have been officially granted temporary protected status, a development that carries substantial consequences for their ability to avail themselves of crucial services such as healthcare, education, and employment opportunities within the host nation. In order to enhance the process of assimilating refugees into their respective host communities, there has been a notable transition in the discourse surrounding policy deliberations. The current emphasis has shifted towards the concept of "harmonization" as opposed to "integration." The deliberate selection of this linguistic preference is intended to further the notion that refugees possess the capacity to reside amicably and make constructive contributions to their host communities.

In accordance with this methodology, Turkey implemented a national strategy for harmonization and devised an action plan in the year 2018. The implementation of this strategic maneuver was undertaken with the principal objectives of augmenting public safety and cultivating local unity. Turkey aims to foster an inclusive atmosphere that promotes harmonious coexistence between short-term residents and foreign nationals, thereby safeguarding the welfare of all individuals within the community.

Also, with the release of the Joint Action Strategy and the EU-Turkey Resolution in 2015 and 2016, respectively, the EU contributed six billion euros to assist Turkey in meeting the needs of refugees. The EU supports initiatives that broaden the opportunities for health care, education, and employment for refugees. In this context, however, policy uncertainty arose, causing integration challenges for Syrian immigrants that sometimes proved fatal [61]. Practical obstacles, such as registration (longer registration wait times) and language barriers (low Turkish competency), make it difficult for Syrians to exercise their legal, medical, and educational rights. It has been shown that establishing and maintaining social ties is just as crucial to a person's well-being as meeting their material demands [62, 63]. The Istanbul Metropolitan Municipality performed a study that found that economic opportunities, social connections, and a feeling of security were the most important factors in bringing Syrian refugees to Istanbul.

In response to the growing humanitarian crisis, both domestic and international nongovernmental organizations (NGOs) in Turkey have begun to focus their efforts on assisting refugees and migrants. Aras and Duman [64] state that NGOs are crucial in

providing refugees with services such as enrollment, legal help and repatriation, language study and training, job placement and living expenses, and capacity building support.
Humanitarian aid was initially provided to Syrian refugees in 2011 by local and international non-governmental organizations (NGOs) in coordination with the Syrian the administration's Tragedy and Crisis Management Presidency (AFAD). The Emergency Protection Law, issued by the Turkish government in 2014, granted legal protection to Syrian refugees, necessities, and protection from being forced to leave Turkey. We can infer that beginning in 2014, humanitarian NGO activities were implemented as part of Turkey's Temporary Protection Law policy. Their initial focus was on economic empowerment, but later their efforts expanded to include social inclusion as well. After 2015, several NGOs began prioritizing the promotion of social cohesion, and they began implementing initiatives in support of government policies. In the field of education, for example, the government has enacted policies that make it easier for Syrians to enroll in school, and non-governmental organizations have created anti-discrimination training programs for educators. The employability of Syrian refugees has been boosted thanks to the training offered by non-governmental organizations, who have also helped with the application of existing laws. The European Union's Resettlement Assistance Fund in Turkey is example of how foreign financing has been routed through NGOs and into the refugee issue. [65] Non-governmental Organizations (NGOs) are involved in the program's implementation.

After the Syrian Civil War, non-governmental organizations operating in Turkey shifted their focus from emergency aid to working with the government to improve the lives of refugees and the communities they settled in. One study found that NGOs, via their work providing essential services and connecting host and refugee communities, significantly aided the establishment of social integration.

2.3 HEALTH SUPPORT MODALITIES

Significant modifications have been made to healthcare systems in countries with large migrant or refugee populations to meet the demands of these new patients (WHO-immigration). The advantages and disadvantages of each model.

a. In the general population, where the public health care system is used.
b. Specialized-Focused, where people first interact with a specialized flow of services tailored refugees' and migrants' health care requirements.

c. Access to primary care services, even if just through a preliminary screening.

d. Only when third-party providers offer mandatory medical services.

The fifth type of model incorporates features from the preceding four. These countries and Turkey, NZ, Can, and the US all employ a hybrid system.

Care for the Syrian refugee group in Turkey has shifted to have a distinct emphasis and gateway. All primary and secondary healthcare services are free for Syrians who register for temporary protection with the UNHCR or the Turkish government. Migrant Health employs Syrian doctors to provide care that is sensitive to patients' cultural backgrounds and provides these to hospital patients at no cost. As of this past June, there were 183 migrant health facilities across Turkey's 29 provinces. Digital Platform and the United Nations High Commissioner for Refugees' World Compact on Refugees. The United Nations High Commission for Refugees (UNHCR) is headquartered in Geneva.

Accessible at "https://globalcompactrefugees.org/article/migrant-healthcenters" (Geneva, 2019). Health care is restricted for illegal immigrants. Considering the current COVID-19 pandemic, however, the president has issued an order guaranteeing temporary access to PPE, diagnostic testing, and medical care for everyone, regardless of their health insurance status. Medically vulnerable foreign nationals in Turkey are classified as stateless [66].

The health repercussions of immigration, whether forced or voluntary, have been a worry for millennia, and modern tidal surges are just one example. After devastating cholera outbreaks raced through Asia, Europe, and USA in the middle of the nineteenth century, the International Sanitary Conferences were held [the predecessor to the contemporary International Health Regulations [67].

The health of migrants is often overlooked in more serious conversations on migration, and they are often left out of efforts to promote health and avoid disease [68]. Concerns over the spread of communicable illnesses are giving way to a greater willingness with nations realizing they need to defend their people' health and human rights, it's time to tackle the larger health concerns encountered by new migrants and refugees. A World Compact on Migration is planned to be approved at a worldwide migration conference in 2018, after debates and discussions launched by the second Annex of the Declaration of New York [69]. Health isn't one of the [70] areas singled out for enhanced priority in the Global Compact, as requested by Decision A/71/L.58 of the UN General Assembly. According to the International Organization for Migration (IOM), several of the Sustainable Development

Goals and Targets outlined in Agenda 2030 [71] would improve the lives of migrants. This is due to the fact that global human rights standards [73] and the World Health Assembly's Law [74] provide a separate normative footing for migrant and refugee heath rights.

The WHO supports policies that work toward this purpose [74], as doing so is essential to protecting the rights of refugees, migrants, and host communities.

The Sustainable Development Goals of the UN reflect the pose no one behind" principle, but providing migrants and refugees with universal health care will require based on proof, inclusive policies that consider the pros and cons of "being healthy for all" from public view health and development viewpoints. [75]. There may be a need for public health governance structures to arise at a level lower than the WHO [76].

Cities have a significant effect on how migrants in Turkey access health services because 98.8 percent of registered refugees live in them, and most COVID-19 cases are recorded there [77]. Applicants for temporary protection, for instance, are restricted to living in big cities like Istanbul, Ankara, and Izmir until they are transferred to a satellite city [78]. They can lose access to the free medical treatment offered in the nearby satellite cities if they do. Pandemics or city epidemics are overseen by local public health experts and political elites. Cities are sometimes examined for their role in disease outbreaks, but regulations are more commonly enacted at the national or international level. Pandemic responses can be hampered by ineffective leadership, poor preparation, and fragmented healthcare systems. As a result, municipal governments need access to equipment suitable for responding to health crises.

To voice urban concerns more effectively on a global scale, cities might band together to form multi-city coalitions. Prior to the COVID-19 epidemic, free healthcare had been created in Turkey's satellite cities. There was no difference in healthcare access between Turkish nationals and those with temporary protection in satellite cities before the new law was implemented at the end of 2019. The worsening economic situation in Turkey in the months leading up to the COVID-19 epidemic played a role in these shifts. Turkey's inflation, joblessness, and currency depreciation all began in 2018 [79].

Proof of public or private health insurance coverage is required for immigrants seeking residency visas. However, most undocumented immigrants must spend out of money for all of their medical care, including in emergencies. Family Health Centre and Migrant Health Centre (MHC) guarantee free primary healthcare (PHC) to all migrants, regardless of immigration status. What we call "primary health care," or PHC, encompasses both prophylactic and curative services, as well as regular contact with populations like expectant and new mothers. Mobile health clinics (MHCs) are being used as part of the SIHHAT initiative, which was developed by the European Union & Turkey to improve the health of Syrians living under temporary protection in Turkey. The initiative aims to improve the availability of healthcare for Syrian refugees. With EU funding, the WHO and the Ministry of Health constructed 180 MHCs in 29 different cities. The Turkish Ministry of Health has employed 1,300 Syrian healthcare professionals to serve in these MHCs by the end of 2019 to ensure that patients receive care that is both linguistically and culturally acceptable. A small number of MoH outpatient facilities in other locations provide free care to refugees from countries other than Syria [80].

Although no one is ever denied access to an emergency room, those without medical insurance will be required to pay in full before they are released. Patients with health insurance will be expected to submit a modest co-payment regardless of whether they are admitted to the hospital or treated as an outpatient. The whole price of the service is due regardless of whether the patient has health insurance.

2.4 ARITIFICIAL INTELLIGENCE BASED APPROACHES

Numerous articles [81–84] were published throughout the 2015–2016 academic year, discussing the political and economic effects of the influx of migrants into Europe. Research and writings that detail the typical behavior of migrants en route to Europe are thus particularly relevant.

For refugees making their way across the Balkans, smartphones were essential for maintaining contact with loved ones back home. They use it to talk to one another, learn new things, and make connections with people like smugglers who can help them get where they're going. They can also coordinate their travel, point out key landmarks, and get back on track if they get lost. These days, social media is often the first point of contact between people. Those who have been forced to evacuate are increasingly turning to social media, particularly Facebook, Twitter, and Instagram [85]. However, refugees are reluctant to utilize social media for fear of being monitored by groups, governments, and coast guards. They will need a passport and a current address to depart the country. Because of this, they frequently disable groups using unencrypted public channels [86]. Previous research has mostly concentrated on the refugee crisis and their health [87-91]. 2012 saw the introduction of convolutional neural networks (CNNs) by LeCun [92], which demonstrated promising results in a variety of software for identifying and categorizing objects. With their development (ILSVRC) [93].

By taking cues from mammalian visual systems, CNNs may take advantage of a process called "end-to-end learning," in which the model learns representations of characteristics and adjusts parameters simultaneously to generate the final output. Examples of how CNNs might be utilized in remote sensing include item detection on the ground [96, 95], determining land use and cover [95, 94], and urban planning [94]. Information is retrieved using convolutional filtering with fixed-size receptive fields, and the central prediction pixel is learnt patch by patch. When a CNN model's patch size is bigger than the item's actual size, it tends to smooth out the edges of the object. CNN's models frequently fail to notice or even completely disregard refugee tents.

Furthermore, patch-wise CNN models do not make use of image semantics during the object recognition stage. Using FCNN, the author of article [97] recommends searching satellite images of refugee camps for signs of human habitation. Conventional FCN models rely on CNNs' convolutional layers to generate rough feature maps. The up-sampling deconvolution layers are then used to construct label mappings at the pixel level for the whole input picture. The FCN uses full-chain, pixel-by-pixel inference to conduct semantic segmentation on pictures of varying sizes. When producing a segmentation result, a trained FCN takes into account the two types of spatial and temporal details in the input picture. The FCN can easily remove several unimportant objects from a picture without proposing areas.

As far as we can tell, the CNN model has not been employed in any studies that aim to explicitly detect refugee faces. Previous refugee research mainly concentrated on the health of Turkish immigrants and the use of the CNN technique to locate refugee tents. Our proposed recurrent neural network (CNN) architecture consists of a fully connected layer, many hidden layers, and a layer called convolutional. The CNN model did exceptionally well in this test, identifying individual migrants even when they were in big groups. Table 2.1 summarizes this section and highlighted the main key points of the past studies.

Table 2.1: Summarized Table of Artificial Intelligence Based Approaches.

Key Points	**Reference**
Smartphones are vital for refugees, aiding communication and travel coordination. They often use social media, but privacy concerns persist.	[85]
CNNs (Convolutional Neural Networks) introduced by LeCun in 2012 show promise in object identification and categorization [92].	[92]
CNNs can utilize "end-to-end learning" inspired by mammalian visual systems, allowing simultaneous feature learning and parameter adjustment [93].	[93]
CNNs have applications in remote sensing, including item detection, land use, and urban planning [94-96].	[94-96]
FCN (Fully Convolutional Network) models enable semantic segmentation in images, preserving spatial and temporal details [97].	[97]
Existing research mainly focuses on refugee health and locating refugee tents; CNNs have not been applied to refugee face detection.	[87-91]

3. METHODOLOGY

In this thesis, we investigate the potential of an AI system for tracking down migrants. The proposed approach is phased, allowing for continuous monitoring of refugee whereabouts. The researchers in this study used an AI-based approach to search for and positively identify refugees in open regions. The immigrant will receive a reminder from the AI system to check in on their location at a specified time. After 10 days, the refugee will be deemed to have left illegally to avoid being apprehended by security, and security will be contacted. There has never been an effort made to employ an AI-based method to locate and follow refugees in Turkey before.

Table 3.1 provides a description of the procedures involved with migrants and refugees at international checkpoints. Each step is described in full below.

a. Migrants and refugees at borders:

a. At this moment, refugees are making their first trip across the boundary into Turkey.

b. Data Collection from Refugees:

b. This involves security personnel at the border conducting interviews with Refugees to get relevant information about them.

c. Each refugee's name, photo, and contact information are recorded in the database:

a. All the collected data about refugees, such as their names, photos, and contact information, is saved in a SQLite3 database.

d. Provide software download link via phone number:

c. The phone numbers of the migrants are supplied a link to an internet-based software.

d. The refugees can use this link to access the software.

e. The displaced person signs up by clicking the link:

a. Refugees click on the provided link to access the software/application, then sign up for an account and log in.

f. Additional details such as the full name, residences, and other PII of the refugee are added:

b. Refugees must now disclose more personal information, including their complete name, address, names of any immediate family members, CNIC (Computerised National Identity Card), and other pertinent information.

g. Information about refugees saved in the database:

c. The database stores all the information provided by the refugees, including the sensitive information mentioned before.

h. Utilizing refugee photo data to train an AI model:

a. Data interpretation training for an AI model utilizing gathered photographs of refugees and non-refugees.

b. The goal of this stage is to train an Artificial Intelligence (AI) model, specifically a Convolutional Neural Network (CNN), to accurately recognise and classify refugee and non-refugee images.

i. Face recognition is powered by AI in every security and public transit area:

d. The trained AI model with face recognition skills is installed in security cameras positioned in public transportation zones.

e. This enables the AI model to detect and identify refugees in real-time.

j. When an AI detects a refugee, it will alert the system and convey the refugee's current position:

a. If the AI model discovers a refugee, the technology sends an SMS (text message) including the refugee's location information to both the refugee and security officials.

k. Text instructions to refugees on how to use their phone's associated software to conduct face and fingerprint recognition:

a. The SMS instructs the refugee to check in to the system using the given software on their phone and update their current location if they have not been identified by the system for two days in a row.

b. The SMS gives the refugee instructions on how to update their location and log into the system using the software that is provided on their phone.

c. The system notifies security personnel, who then take appropriate action against the refugee, if the refugee does not react within 10 days.

As a whole, this process entails collecting data, storing it, and employing facial recognition technology powered by artificial intelligence in order to control the flow of refugees and increase security.

Table 3.1: Description of Proposed Methodology Steps.

No. of steps	**Stages**	**Description**
1	Border issues with refugees and migrants	At the border, the refugees entered Turkey.
2	Refugee Information Gathering	Border patrol collects information about refugees.
3	Each refugee's name, photo, and contact information are recorded in the database	Information about the refugees, including their names, photos, and phone numbers, is kept in a SQLite3 database.
4	Provide software download link via phone number	The refugees' phone numbers are texted the link to an internet-based application.
5	The displaced person signs up by clicking the link	Clicking the provided link and signing in allows refugees to join the program.
6	Additional details such as the full name, residences, and other PII of the refugee are added	Upon request, refugees are obligated to provide identifying details (such complete name, residence, and family).
7	The repository contains information on refugees	The database stores every information submitted.
8	Utilizing refugee photo data to train an AI model	Both refugee and non-refugee photos are used to train a CNN model for data interpretation.

Table 3.1: Description of Proposed Methodology Steps" Table Continued".

9	Face recognition is powered by AI in every security and public transit area	To perform facial recognition, the trained AI model is integrated in the surveillance systems of public buildings and public transit.
10	When an AI detects a refugee, it will alert the system and convey the refugee's current position	The technology a text message to the asylum seeker and security personnel informing them of the refugee's location if an AI model detects a refugee.
11	Text instructions to refugees on how to use their phone's associated software to conduct face and fingerprint recognition	A message is delivered to the refugee's phone after two days if they haven't logged in to update their whereabouts. After 10 days, security personnel will act against the refugee.

The proposed procedure is broken down into several discrete steps. This study contributed technically by proposing the deployment of an artificial intelligence-based strategy to track down and identify refugees. The use of AI to track down and identify evacuees is still in its infancy. The proposed strategy utilizes a preexisting CNN model in tandem with transfer learning. This work enhances the VGG16 model, a CNN version, by incorporating statistics on displaced people in Turkey. The VGG16 model's initial training phase made use of a big collection of actual photographs. Finally, transfer learning is used in this investigation. This innovative method significantly reduces the time required to train on a small dataset, paving the way for the development of an effective system for the identification of refugees and migrants in Turkey utilizing CNNs.

3.1 METHODS AND MATERIAL

The process of verifying the identities of the refugees is described here. In the first stage, information about migrants and refugees entering Turkey across the border was recorded. Refugees and non-refugees alike had their faces photographed for this study. Personal data including names, addresses, phone numbers, and even fingerprints may be taken from refugees at the border. Massive amounts of information can be stored in Sqlite3 databases. Sqlite3's data storage strategy was rational. In logical design, data is broken down into its component elements, called entities and attributes. A single record or "entity" in a database. The traits that make a thing unique from others are what define it. Entity-table relationships are common in relational databases. To better understand the requirement and the interplay between entities and their properties, a logical framework is developed. Figure 3.1 depicts a logical design.

The next step was to integrate the software with a list of refugee contact numbers. When applying for the program, refugees are asked to enter personal details such as names, residences, CNICs, and family composition. This data is stored in a database somewhere. The system is an online repository for refugee information.

Applying a variety of deep convolutional neural networks (CNNs) (including Vgg16, InceptionV3, and vgg19), the recommended method surpasses previous methods via transfer learning when identifying images. Data augmentation is a technique for improving the quality of a model's outputs by including more data in the training datasets. Three distinct data sets—for training, validating, and then testing—were generated. Features are derived from the training and validation sets by a CNN model. In order to train models for object detection in photos, We used CNNs together with InceptionV3 and Vgg16 and Vgg19 from the deep learning family. Trainability, testability, accuracy, recall, an F1-s confusion matrix, and ROC AUC were all measured for the suggested transfer learning-based model and compared to those of state-of-the-art CNN variations.

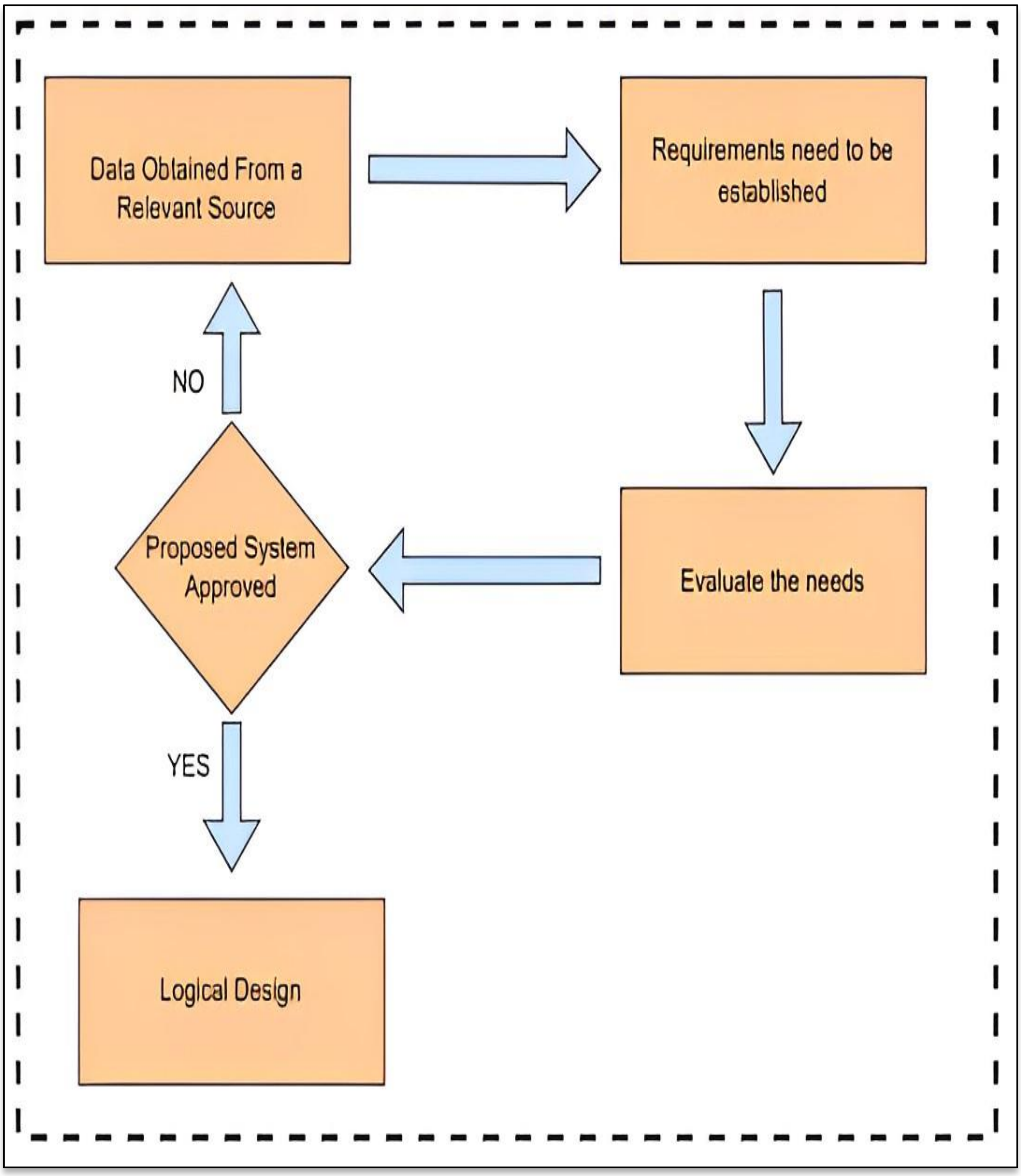


Figure 3.1: Design the Data Modelling Guidelines.

3.1.1 Dataset Creation and Annotation

The most important information for developing and evaluating a model must be collected before training can begin. The models were trained using only a subset of the original image data. Images of refugees can be seen in a wide variety of places. The picture is in PNG format. We also gathered and captioned photographs of people who were not refugees. The general population and the refugees are the two components of this civilization. Both typical citizens and refugees can be seen in the image datasets. To train the model, 140,002 photos were used; to validate it, 39,428 were analyzed; and to test it, 10,905 were analyzed.

3.1.2 Data Pre-Processing

When utilizing CNNs for image classification, a lot of time must be spent on preprocessing the input images. Two of the many tasks that must be taken now are scaling and adding more data.

Since images can be any size or shape, it's difficult for CNNs to understand them. For the sake of consistency for the model and the computer, it is common practice to reduce the size of all images to the same, often lower, size. Images are reduced in size so that they will fit inside a 2562563 grid.

Knowing that image-based refugee-finding systems have difficulties related to the need to be more particular and the capacity for effective generalization, we improved the photographs in several ways ("Data Augmentation"). In this study, image augmentation is used to create new images with enhanced features including rotation, zoom, and translation. This technique significantly lessens the likelihood of over-fitting. In this study, authentic face trace characteristics were recognized through the deformation of human faces the Kera's framework's Vision Data Generator. Random horizontal flipping, magnification, and rotation are the most often used methods for achieving these adjustments. Our data was modified in the following ways: The picture size was set to 256x256, the rotation range was set to 25, the shear range was set to 0.2, the zoom range was set to 0.2, and the horizontal flip on option was activated. And then, number six, we switched to a setting called "nearest fill." The width fluctuation range was reduced to 0.1, and the height variation range was reduced to 0.1 as well.

The implementation of image data augmentation is presented in the Figure 3.2a. It is evident that data augmentation has been implemented on a dataset intended for a binary classification problem, leading to an unequal distribution of photos across the two classes. The numbers in question are likely to indicate the following:

The dataset consists of a total of 140,002 photos, which are categorized into two distinct classes. The aforementioned observation suggests that following the use of data augmentation techniques, the dataset now has a total of 140,002 photos. These images have been segregated into two distinct classes.

The dataset consists of a total of 39,428 photos, which are categorized into 2 distinct classes. This implies that a specific portion of the dataset, comprising 39,428 photos, is also categorized into two separate classes. This particular subset could potentially be employed for the purposes of validation or testing.

The dataset consists of a total of 10,905 photos that are categorized into 2 distinct classes. The aforementioned numerical values correspond to an additional subset inside the dataset, comprising a total of 10,905 photos that have been classified into two distinct categories. This particular subset could be allocated for evaluating the performance of the trained model. The dataset has been extended, presumably with the intention of enhancing its diversity and bolstering the model's capacity for generalization. The dataset has been appropriately partitioned into training, validation, and testing sets for the purpose of conducting machine learning or deep learning experiments.

```
image_gen = ImageDataGenerator(
    rescale=1./255.
)
batch_size = 64
train_flow = image_gen.flow_from_directory(
    base_path + 'Train/',
    target_size=(256, 256),
    batch_size=batch_size,
    class_mode = "categorical"
)
valid_flow = image_gen.flow_from_directory(
    base_path + 'Validation/',
    target_size=(256, 256),
    batch_size=batch_size,
    class_mode = "categorical"
)
test_flow = image_gen.flow_from_directory(
    base_path + 'Test/',
    target_size=(256, 256),
    batch_size=1,
    shuffle = False,
    class_mode = "categorical"
)
```

```
Found 140002 images belonging to 2 classes.
Found 39428 images belonging to 2 classes.
Found 10905 images belonging to 2 classes.
```

Figure 3.2: Data Augmentation Implementation.

3.1.3 Feature Extraction

A Convolutional Operator is useful for simplifying problems. Time-domain data and images are just two types of inputs that a convolutional network may process. During training, it collects features and sets weights. CNNs' primary benefit is its capacity to automatically extract features. A feature extractor network and a classifier inferring network work together to process an input image. To get the most useful information out of the data, it is common practice to combine convolutional and pooling layers throughout the feature extraction process. At every convolutional stage of the digital filter, the input data is subjected to a convolution operation. The threshold is determined in the dimensionality-reduction pooling layer. Because of the requirement to adjust a few parameters during backpropagation, the degree of connection in a neural network is generally lowered. Thanks to this, we were able to glean the precise data we need from the photos.

3.1.4 Modeling

Convolutional neural networks (CNNs) are widely used in the area of deep learning, especially for image recognition. The numerous components that make out the whole will be discussed in greater depth in subsequent chapters. The input picture is processed by the CNN model, which consists of layers of convolution, layers of pooling, and fully connected layers. The layer of convolution takes in both the core size and the picture size as inputs. Layer pooling allows feature maps to retain their depth while losing height and width. Maximum pooling is used in the model of our convolutional neural network. The nodes of a layer can produce classes when they are interconnected. To complete the binary classification, we utilized a Soft Max activation algorithm in the last layer. The Adam optimizer was utilized by the CNN model to determine the extent of the loss. Eighty percent of the photos were utilized for training a convolutional neural network (CNN), ten percent were used to verify the network's accuracy, and the remaining twenty percent were used for testing. The main parts of a CNN model are shown in Figure 3.2b.

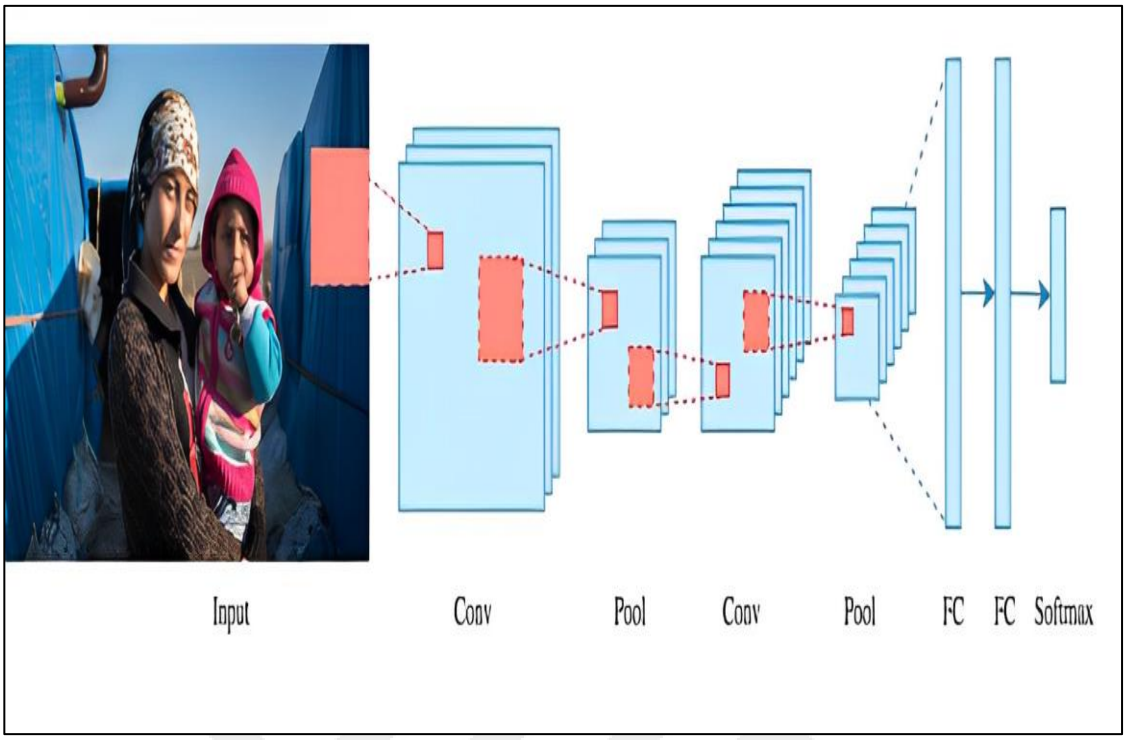


Figure 3.3: Convolutional Neural Network Architecture.

3.1.5 Cnn Model Architecture

This CNN model shown in Figure 3.3 was created to perform picture categorization tasks. It is made up of numerous layers that handle input data in a sequential manner.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
batch_normalization (BatchNo (None, 256, 256, 3)       12
_________________________________________________________________
conv2d (Conv2D)              (None, 256, 256, 16)      448
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 128, 128, 16)      0
_________________________________________________________________
batch_normalization_1 (Batch (None, 128, 128, 16)      64
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 128, 128, 32)      4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 64, 64, 32)        0
_________________________________________________________________
batch_normalization_2 (Batch (None, 64, 64, 32)        128
_________________________________________________________________
dropout (Dropout)            (None, 64, 64, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 64, 64, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 64)        0
_________________________________________________________________
batch_normalization_3 (Batch (None, 32, 32, 64)        256
_________________________________________________________________
dropout_1 (Dropout)          (None, 32, 32, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 128)       73856
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 16, 16, 128)       0
_________________________________________________________________
batch_normalization_4 (Batch (None, 16, 16, 128)       512
_________________________________________________________________
dropout_2 (Dropout)          (None, 16, 16, 128)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 16, 16, 256)       295168
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 8, 8, 256)         0
_________________________________________________________________
batch_normalization_5 (Batch (None, 8, 8, 256)         1024
_________________________________________________________________
dropout_3 (Dropout)          (None, 8, 8, 256)         0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 8, 8, 512)         1180160
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 4, 4, 512)         0
_________________________________________________________________
batch_normalization_6 (Batch (None, 4, 4, 512)         2048
_________________________________________________________________
dropout_4 (Dropout)          (None, 4, 4, 512)         0
_________________________________________________________________
global_average_pooling2d (Gl (None, 512)               0
_________________________________________________________________
dense (Dense)                (None, 48)                24624
_________________________________________________________________
dropout_5 (Dropout)          (None, 48)                0
_________________________________________________________________
dropout_6 (Dropout)          (None, 48)                0
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 98
=================================================================
Total params: 1,601,534
Trainable params: 1,599,512
Non-trainable params: 2,022
_________________________________________________________________
```

Figure 3.4: CNN Model Architecture.

Batch Normalization (batch normalization): The model begins with a Batch Normalization layer, which normalizes the input data and improves training stability and efficiency. It features a total of 12 trainable parameters.

Layers of Convolution (conv2d, conv2d_1, conv2d_2, conv2d_3, conv2d_4, conv2d_5): The CNN's core consists of six convolutional layers. Convolutional layers collect features from input data by applying filters to it. These levels progress in depth, with the first layer including 16 filters and the ultimate layer containing 512 filters. Each filter learns to distinguish various data patterns, such as edges or textures.

max_pooling2d,max_pooling2d_1,max_pooling2d_2,max_pooling2d_3,max_pooling2d_4 , max_pooling2d_5):

Following each convolutional layer, a Max-Pooling layer decreases the spatial dimensions of the data. While lowering computing complexity, Max-Pooling keeps the most relevant information. The data is gradually down sampled by these layers.

Layers of Dropout (dropout, dropout_1, dropout_2, dropout_3, dropout_4, dropout_5, dropout_6):

Dropout layers are inserted after some of the Max-Pooling layers to prevent overfitting. Dropout deactivates a subset of neurons at random during training, driving the model to learn more robust characteristics.

Global Average Pooling (global_average_pooling2d): This layer averages the values of the last convolutional layer's feature maps, reducing the spatial dimensions to a single value for each feature map. It's a type of spatial pooling that gets the data ready for the final classification layers.

Layers that are totally connected (dense, dense_1): The last layers are fully connected. The initial dense layer has 48 neurons, while the final dense layer contains only two neurons, indicating a binary classification problem with two classes. These layers are in charge of making the ultimate predictions and judgments.

Total parameters: The model has a total of 1,601,534 parameters, 1,599,512 of which are trainable. The non-trainable parameters are most likely the Batch Normalization layers.

Compilation: The model is compiled with binary cross-entropy as the loss function, Adam as the optimizer and a learning rate of 0.01, and numerous evaluation measures such as accuracy, precision, recall, F1-score, and AUC. It is set up for binary categorization, having two classes.

Training: The model is trained for 7 epochs, which means it travels over the full training dataset seven times. The purpose of training is to optimize the model's parameters in order to reduce the binary cross-entropy loss and enhance the model's ability to correctly categorize images.

This CNN architecture is appropriate for image classification applications and employs techniques like as Batch Normalization, Max-Pooling, Dropout, and Global Average Pooling to improve performance and reduce overfitting during training.

3.2 VGG16 MODEL ARCHITECTURE

The architectural design of the model is characterized by its sequential nature, wherein the layers are arranged in a linear stack. The CNN model under consideration exhibits a clear foundation in the VGG16 architecture, which is widely recognized for its efficacy in image categorization endeavors. The following is an analysis of each layer and its corresponding configuration:

The VGG16 model, implemented using functional layers, is utilized in this study as shown in Figure 3.4.

The initial layer corresponds to a functional layer that embodies the architectural design of VGG16. The VGG16 model is a widely recognized deep convolutional neural network that is frequently employed for the purpose of picture classification. The architecture consists of a total of 14 convolutional layers, which are subsequently followed by fully linked layers. The output shape of the model is (None, 8, 8, 512).

The given criteria: The VGG16 architecture is comprised of about 14 million parameters, although the specific details of these parameters are not included in this summary.

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Functional)           (None, 8, 8, 512)         14714688
_________________________________________________________________
flatten (Flatten)            (None, 32768)             0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               8388864
_________________________________________________________________
dropout_7 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 514
=================================================================
Total params: 23,104,066
Trainable params: 23,104,066
Non-trainable params: 0
_________________________________________________________________
```

Figure 3.5: VGG16 Model Architecture.

The flattening layer is a component in neural networks that transforms multidimensional input data into a one-dimensional array.

The function of this particular layer is to transform the output generated by the VGG16 layers into a flattened representation, resulting in a one-dimensional vector. The output shape of the model is represented as (None, 32768). The process of flattening is commonly performed prior to feeding data into fully connected layers. The dense layer, sometimes known as dense_2, is a component of a neural network architecture.

The layer under consideration is a fully linked layer comprising 256 neurons.

The output shape is represented as (None, 256). The layer under consideration possesses a total of 8,388,864 trainable parameters, encompassing both weights and biases. The dropout layer, denoted as dropout_7, is a component used in neural networks for regularization purposes.

The application of dropout is typically implemented following the thick layer in order to mitigate the issue of overfitting. During the training process, a subset of neurons is randomly deactivated. The shape of the output is represented as (None, 256). There are no extra trainable parameters included in this layer.

The Dense Layer, often known as dense_3, is a component of a neural network architecture. The present layer is the ultimate completely linked layer comprising of two neurons, signifying a binary classification task including two distinct classes. The output shape is represented as (None, 2).

In this layer, there are a total of 514 trainable parameters, which include weights and biases. The model as a whole consists of a total of 23,104,066 parameters, all of which are capable of being trained. This encompasses the parameters derived from the VGG16 layers as well as the two dense layers.

Non-trainable parameters refer to the components within the model that are associated with the VGG16 architecture, namely comprising pre-existing weights. The aforementioned parameters remain fixed during the training process.

The configuration for training.

The model undergoes three epochs of training, wherein it iterates through the complete training dataset on three separate occasions. The loss function employed in this study is binary cross-entropy, which is commonly utilized for binary classification problems. The Adam optimizer is employed in conjunction with a predetermined learning rate and decay rate. The learning rate is initially set to "initial_lr" and is subsequently reduced during the training epochs in order to enhance the convergence of the model.

Various evaluation metrics are employed during the training process, encompassing accuracy, precision, recall, F1-score (micro-averaged), and AUC.

The architecture of this CNN is derived from the VGG16 model and has been specifically designed for the purpose of binary image classification. The approach utilizes a pre-existing model to extract features, then subsequently refines the final dense layers to cater to the specific classification objective.

3.2.1 InceptionV3 Model Architecture

The architectural design shown in Figure 3.5 employed in this study is a Sequential model, characterized by a linear arrangement of layers. The utilization of the InceptionV3 architecture, a widely recognized deep convolutional neural network, is employed for the purpose of picture categorization tasks. The following is an analysis of each layer and its corresponding configuration. The functional layer of InceptionV3.

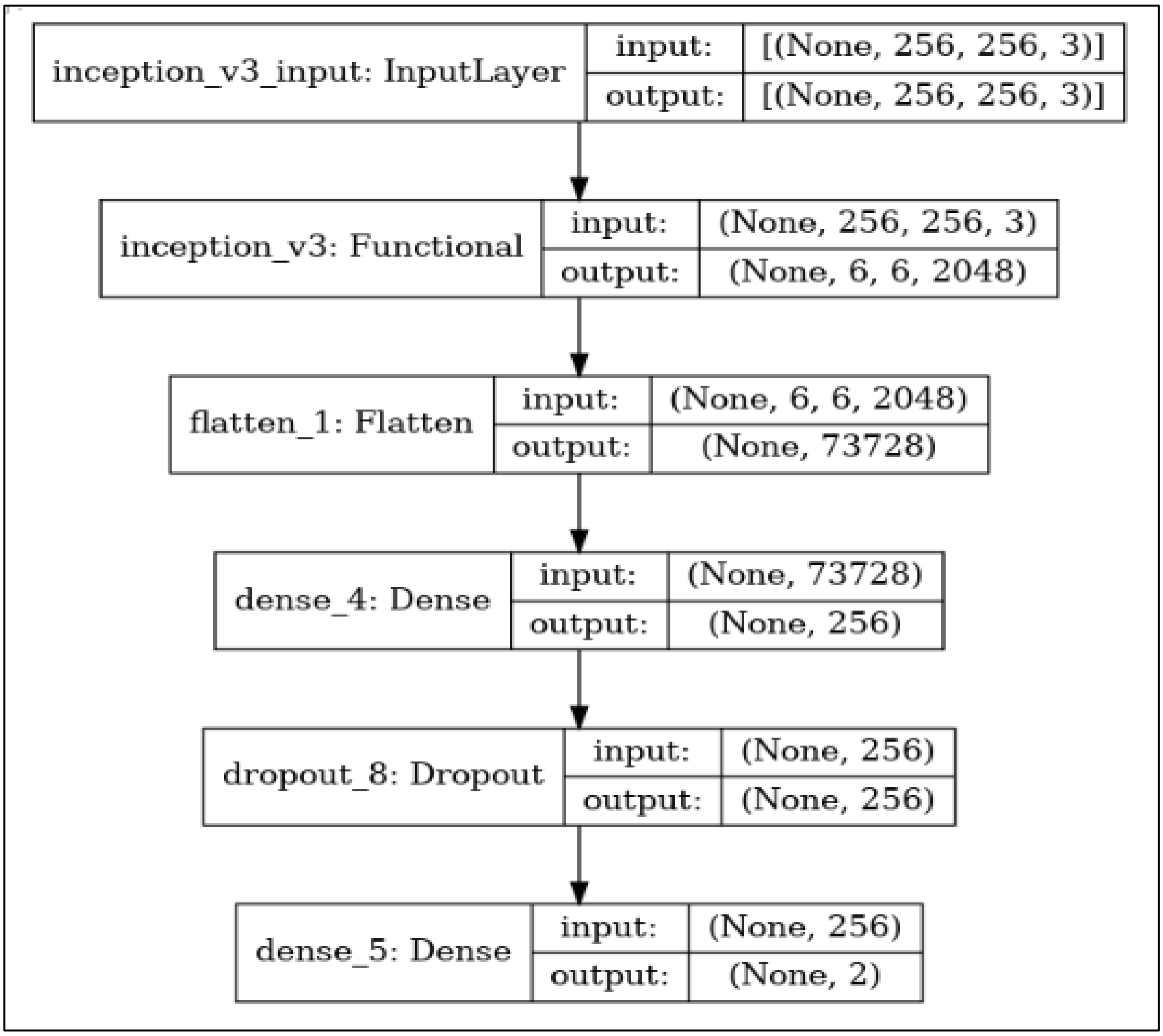


Figure 3.6: InceptionV3 Model Architecture.

The initial layer corresponds to a functional layer that embodies the InceptionV3 design. The InceptionV3 architecture is widely recognized in the field of computer vision for its superior performance in image classification tasks, owing to its intricate convolutional neural network design that combines both efficiency and accuracy. The output shape of the model is (None, 6, 6, and 2048). The InceptionV3 architecture is comprised of about 21,802,784 parameters, although the specific details of these parameters are not provided in this report. The Flatten Layer, also known as flatten_1, is a component used in neural networks to transform multi-dimensional input data into a one-dimensional array. The function of this layer is to transform the output generated by the InceptionV3 layers into a singledimensional vector. The output shape of the data is represented as (None, 73,728). The process of flattening is commonly performed prior to transmitting data to fully linked layers. The dense layer, denoted as dense_4, the layer in question is a fully linked layer consisting of 256 neurons. The output shape is represented as (None, 256). The number of trainable parameters in this layer is 18,874,624, which includes both weights and biases. The dropout layer, referred to as dropout_8, is a component utilized in neural networks for regularization purposes.

The dropout technique is commonly employed following the dense layer in order to mitigate the issue of overfitting. During the training process, a subset of neurons is stochastically deactivated. The output shape is represented as (None, 256). There are no extra trainable parameters included in this layer. The dense layer, sometimes known as dense_5, is a component of a neural network architecture. The present layer is the ultimate fully linked layer comprising of two neurons, which signifies a binary classification task encompassing two distinct classes. The output shape is represented as (None, 2). The layer under consideration consists of 514 trainable parameters, which include weights and biases. The model as a whole consists of a total of 40,677,922 parameters, all of which are capable of being trained. This encompasses the parameters derived from the layers of the InceptionV3 model, as well as the two dense layers.

The model contains a total of 34,432 non-trainable parameters. The parameters associated with the InceptionV3 architecture are typically comprised of pre-trained weights that remain unaltered during the process of fine-tuning.

The model undergoes four epochs of training, wherein it iterates through the complete training dataset on four separate occasions. The loss function employed in this study is binary cross-entropy, which is commonly utilized in binary classification problems. The term "optimizer" is referred to as "opt" in the given information, but no further elaboration or specifics are supplied.

Various assessment measures are employed during the training process, encompassing accuracy, precision, recall, F1-score (micro-averaged), and AUC.

The CNN employed in this study adopts the InceptionV3 architecture for extracting features from images. Subsequently, the final dense layers of the network are fine-tuned to optimize performance for the specific goal of binary image classification. The model possesses a considerable quantity of trainable parameters, rendering it well-suited for intricate applications.

3.3 VGG19 MODEL ARCHITECTURE

Architecture in Figure 3.6 refers to a structured model comprising various layers, such as convolutional, pooling, and fully linked layers. The present model is constructed upon the VGG19 architecture, a deep convolutional neural network that has gained significant popularity in the field of picture categorization. The following is an analysis of each layer and its corresponding configuration. The input layer, denoted as input_5, is the initial layer of a neural network where the input data is received. The layer in question pertains to the input of the model, commonly used for images that possess three color channels, namely red, green, and blue (RGB). The output form is dependent on the size of the input, while maintaining a consistent number of channels (3). The convolutional layers, namely block1_conv1, block1_conv2, block2_conv1 are integral components of the neural network architecture. The aforementioned layers are accountable for acquiring hierarchical features from the incoming data.

In the context of convolutional neural networks, every convolutional layer is responsible for applying a specific set of filters to the input data. Through this process, the layer is able to acquire and comprehend features at various levels of abstraction. The quantity and dimensions of filters vary across different levels. The shapes of the output in a neural network vary depending on the layer, but typically exhibit a pattern of steadily decreasing spatial dimensions and increasing channel numbers. The convolutional neural network architecture includes max-pooling layers, specifically block1_pool, block2_pool, and so on. Following each sequence of convolutional layers, a max-pooling layer is employed.

Max-pooling is a technique employed in neural networks to decrease the spatial dimensions of the input data while preserving the most significant information. The subject of interest pertains to the many forms and configurations of output shapes. The spatial dimensions of the layers vary, but they are generally reduced. The technique employed in this study is known as Global Average Pooling, specifically global_average_pooling2d_1. The aforementioned layer performs the computation of the mean value for every feature map, considering its spatial dimensions. The result is reduced to a vector with a single dimension, effectively summarizing the acquired features. The output shape is represented as (None, 512). The dense layers, namely dense_6 and dense_7, are components of a neural network model.

The final forecasts are generated by the completely connected layers.

The initial dense layer is composed of 1024 neurons, whereas the last dense layer consists of 2 neurons, suggesting the utilization of a multi-class classification approach involving two distinct classes.

The output shape of the initial dense layer is (None, 1024), whereas the output shape of the last dense layer is (None, 2).

The overall model consists of a total of 20,551,746 parameters, with only 527,362 of these parameters being trainable. The remaining parameters are non-trainable and are most likely linked to the pre-trained weights derived from the VGG19 design.

Non-trainable parameters encompass a total of 20,024,384 in this particular model, signifying the pre-existing weights within the VGG19 architecture. During the process of fine-tuning, it is common practice to freeze these weights.

The model undergoes training for a total of seven epochs, indicating that it iterates through the complete training dataset on seven separate occasions. The loss function employed in this study is categorical cross-entropy, which is commonly utilized in multi-class classification scenarios. The RMSprop optimizer is employed in this study, as it dynamically adjusts the learning rate throughout the training process.

The architecture based on VGG19 is well-suited for problems involving image classification, as it effectively fine-tunes the final dense layers to cater to the unique requirements of the classification task at hand. The utilization of pre-trained weights derived from the VGG19 architecture is advantageous for the purpose of extracting features from images.

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_5 (InputLayer)         [(None, None, None, 3)]   0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, None, None, 64)    1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, None, None, 64)    36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, None, None, 64)    0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, None, None, 128)   73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, None, None, 128)   147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, None, None, 128)   0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, None, None, 256)   295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, None, None, 256)   590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, None, None, 256)   590080
_________________________________________________________________
block3_conv4 (Conv2D)        (None, None, None, 256)   590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, None, None, 256)   0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, None, None, 512)   1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block4_conv4 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, None, None, 512)   0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block5_conv4 (Conv2D)        (None, None, None, 512)   2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, None, None, 512)   0
_________________________________________________________________
global_average_pooling2d_1 ( (None, 512)               0
_________________________________________________________________
dense_6 (Dense)              (None, 1024)              525312
_________________________________________________________________
dense_7 (Dense)              (None, 2)                 2050
=================================================================
Total params: 20,551,746
Trainable params: 527,362
Non-trainable params: 20,024,384
_________________________________________________________________
```

Figure 3.7: VGG19 Model Architecture.

3.3.1 Experimental Setup

Table 3.2 details the computer architecture that was used to train the CNN model.

The table that is provided shows how the experiments were computed; the following is a description of each parameter and its related setting:

3.4 LANGUAGE: PYTHON

a. Python version 3.7 was the research language of choice.
b. Python is a popular programming language for scientific computing, machine learning, and data analysis.

3.5 FRAMEWORK: KAGGLE

a. Kaggle is a popular online community and platform for data science and machine learning competitions, and it provides users with a wide range of resources for conducting data analysis and creating models.
b. The framework parameter indicates that the experiments were carried out using this platform.

3.6 OS: WINDOWS 10

a. It designates Windows 10 as the testing OS.
b. The popular Windows 10 operating system was developed by Microsoft.

3.7 RAM: 16GB RAM

a. RAM (Random Access Memory) refers to the amount of memory that is made available for experimentation.
b. Here, testing was conducted using 16 GB of RAM.
c. The performance of the tests is affected by RAM because of its significance in data manipulation and storage during computing.

3.8 GPU: NVIDIA K80 GPUS

a. The term GPU, or graphics processing unit, refers to a device that speeds up computation, particularly for complex activities like deep learning.
b. Since NVidia K80 GPUs were used in the studies, the computational workload was transferred to them for quicker processing.
c. The GPU model known as the NVidia K80 is distinguished by its capacity for parallel processing.

3.9 PROCESSOR: 2.4 GHZ PROCESSOR

a. The processor parameter specifies the processing unit used for the experiments.
b. In this case, a processor with a clock speed of 2.4 GHz was employed.
c. The clock speed of a processor dictates how many instructions it can carry out per second, which in turn affects how quickly calculations can be performed.

Hardware and software including the CPU, GPU, and operating system, programming language, framework, and amount of Random Access Memory (RAM) employed in the experiments is listed in this table. These specifics are crucial for understanding the computational resources used in the experiments and for achieving reproducibility.

Table 3.2: Experimental Setup CNN Model Training.

Inputs	**Setup**
Python Version	Python 3.7
Platform	Kaggle
OS	Window 10
RAM	16GB
GPU-Version	NVidia K80 GPUs
Processor-Version	2.4 Ghz processor

To make public transportation safer, a CNN model was trained and then employed. All public transportation and security systems are currently using the AI paradigm. When the camera's AI model recognizes a refugee, the system will send them a text message requesting them to check in and update their geolocation data. Additionally, the gadget will notify authorities of the refugee's exact position. If the refugee hasn't logged on or shown on the camera after two days have passed, the system will issue a text message to his phone number, requesting that he get in communication and let us understand where he is. If the refugee does not react within 10 days, the system will continue sending them SMS reminders automatically. The refugee's absence is notified to authorities. The authorities will immediately arrest the uprooted person. There is currently no available software that can track migrant locations in the present moment. There are estimated to be 3.7 million Syrians in Turkey, with a further 5.5 million foreigners. Any refugees who manage to leave the nation will do it illegally. Therefore, it is crucial to have access to an updated database of refugees on a consistent basis. The suggested method makes use of AI-based techniques to reliably identify displaced persons in public places and report on their current safety conditions in real time.

3.10 EVALUATION METRICS

Important indicators for analysis include the recall rate, the accuracy and precision of the data, and the area underneath the receiver's operating characteristic (AUC-ROC) curve. These indicators are priceless when trying to place problems into categories.

The accuracy rate of a model's predictions is a good indicator of the model's credibility. The test's efficacy is determined by the proportion of right answers. However, precision may not be the most significant criteria when there is a huge differential in the amount of data accessible to the two classes, such as when one class is much bigger than the other. For a certain category, "precision" indicates the proportion of accurate forecasts. This metric measures how well the model avoids false positive predictions, in which the model gives a positive prediction while the real class is a negative one.

The recall rate, calculated by tallying the total number of positive samples, provides an indication of how often patients have their test results recalled as positive. This statistic measures a model's effectiveness in producing fewer false negatives. The model makes a wrong prediction of a negative class while the real class is positive; this is called a false negative.

The F1-Score is an average of the three metrics of correct predictions: recall, precision, and accuracy. This method is useful in situations when accuracy and memory are equally crucial. A complete success on this scale would be represented by a score of one.

A confusion matrix is a data table that summarizes the proportions of accurate and erroneous categorizations as well as incorrect classifications and false negatives, for each classification system. Some of the metrics that may be measured by this tool are precision, recall, accuracy, and F1 score.

The area below the graph-ROC curve is obtained by comparing the percentage of true positives (TPR) against the false positive rate (FPR) with various criteria. As the performance of a model using binary classification is measured over a variety of thresholds, its discriminating power may be estimated. On a scale from 0.0 to 1.0, AUC values closer to 1.0 imply better performance. An AUC-ROC of 1.0 is ideal, whereas a result of 0.5 implies little improvement over random classification.

3.11 ADVANTAGES AND DISADVANTAGES OF PROPOSED APPROACH

The primary objective of this research is to enhance convolutional neural networks' skill of identifying foreigners (refugees) in Turkey. The primary motivation for this effort is the search for an automated, scalable solution to the issues of migrant and refugee identification and registration. The research has a wide range of positive implications. Refugees and migrants, whose security is at stake if they are not properly identified and monitored, can rest better knowing that authorities will be able to keep a closer eye on their whereabouts. The second benefit of convolutional neural networks is that they allow for the development of an accurate and effective detection strategy that can greatly lessen the workload of human operators while simultaneously speeding up and bettering the identification process. Finally, the proposed approach is adaptable to a variety of contexts and can be used on a worldwide scale to track down displaced people. The findings could have far-reaching impacts on the identification of refugees and migrants, improving the lives of all people.

Advantages/Why should we use it?

First, the proposed system is more accurate than previous ones in spotting refugees and migrants since it makes use of transfer learning techniques.

Because it can handle large amounts of visual input reliably and quickly, the suggested system has practical and scalability potential.

The suggested method utilizes convolutional neural networks to automatically detect and locate migrants and refugees without the need for human identification or tracking.

The proposed strategy, fourth, is adaptable to many contexts and countries. This adaptability makes it a useful resource for tracing migrants and refugees across borders.

Refugees and migrants could benefit from the proposed method because it would make them simpler to find and track.

Disadvantages/Why should we don’t use it?

The proposed method is, nevertheless, very specialized for the issue at hand of identifying migrants and refugees in Turkey, so it may not be applicable to other image classification issues.

The quality and quantity of the training dataset are what ultimately define the effectiveness of the proposed approach. The dataset is either too small or too biased to make full use of the methods potential.

While these transfer learning approaches can be useful for some photo categorization problems, they are extensively relied upon in the suggested strategy.

The suggested method employs a deep convolutional neural network, which requires significant time and energy to develop and fine-tune.

Concerns about privacy, monitoring, and possible technology misuse arise when automated technologies are used to locate refugees and migrants. To apply the proposed strategy ethically and responsibly, it is necessary to address and mitigate these concerns.

3.12 CHAPTER SUMMARY

Here is a complete description of the processes used to manage refugees and migrants at international checkpoints. The journeys of migrants and refugees typically begin at international borders, in this case the Turkish border. The refugees' personal information is collected by border patrol agents. In order to learn more about each person, they conduct interviews. The migrants' phone numbers are used as access codes to online software that enhances communication and collaboration. Refugees can't make it on the road without this program. Refugees use the link provided to them to download the application or program. To access the materials, they create an account and sign in.

As a result, asylum seekers have to reveal even more information about themselves, including their complete names, current addresses, names of any close relatives, CNIC (Computerized National Identity Card), and any other relevant data. The database stores all the data provided by the refugees, including the sensitive information gathered in the beginning.

To further ensure the safety of everyone, authorities are using images of both refugees and non-refugees to train an AI model, especially a Convolutional Neural Network (CNN). Accurate identification and categorization of refugee and non-refugee photographs is a primary objective. Security cameras installed in public transportation hubs now feature the

trained AI model's facial recognition capabilities. Refugees can now be located and identified in real time because to this integration. As soon as the AI system identifies a refugee, it immediately notifies the main system and reports the refugee's present location.
In addition, the system provides SMS instructions to refugees, teaching them how to install the necessary software for face and fingerprint recognition on their mobile devices. If the system is unable to identify a refugee for two days in a row, that person is urged to update their location.
If no one responds within 10 days, security will step in and take the necessary precautions.
In conclusion, this all-encompassing procedure includes data gathering, storage, and usage, as well as the implementation of facial recognition technology supported by artificial intelligence. To better control the flow of refugees and increase safety at international checkpoints, several procedures have been implemented.

4. EXPERIMENTS AND RESULTS

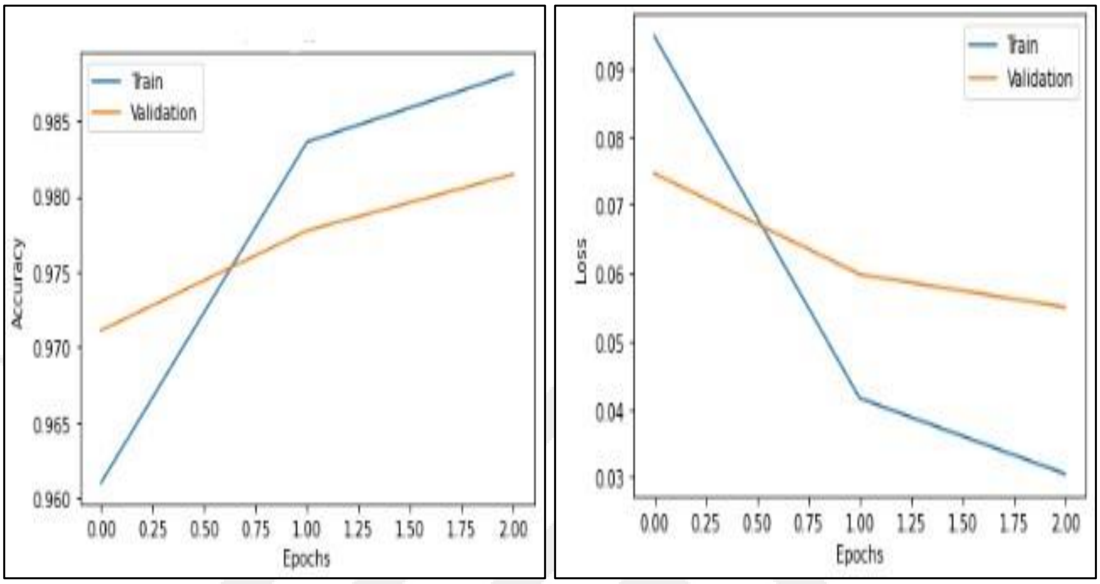
The findings of the study are shown here. This research aimed to apply AI to determine who among the public might be a refugee. That's why we put the CNN model through tests and train it repeatedly. Binary classifications were taught to the models. Then, a visual data generator was employed to make sure our photographs are perfect. The models were also fed the results of a visual data generator used for labeling purposes. The model was trained over the course of twenty epochs. Data sets for training, validating, and testing were developed. Figures 4.1a and 3b display the training results and the verification results, respectively. Accuracy throughout training and validation is shown in Figure 4.1a, while loss during both phases is shown in Figure 4.1b. For this study, we employed Python on an NVidia GPU. Instead of focusing on improving evaluation methods in the hopes of seeing improved outcomes, we are instead working on a method to detect and track down missing migrants.

4.1 RESULTS

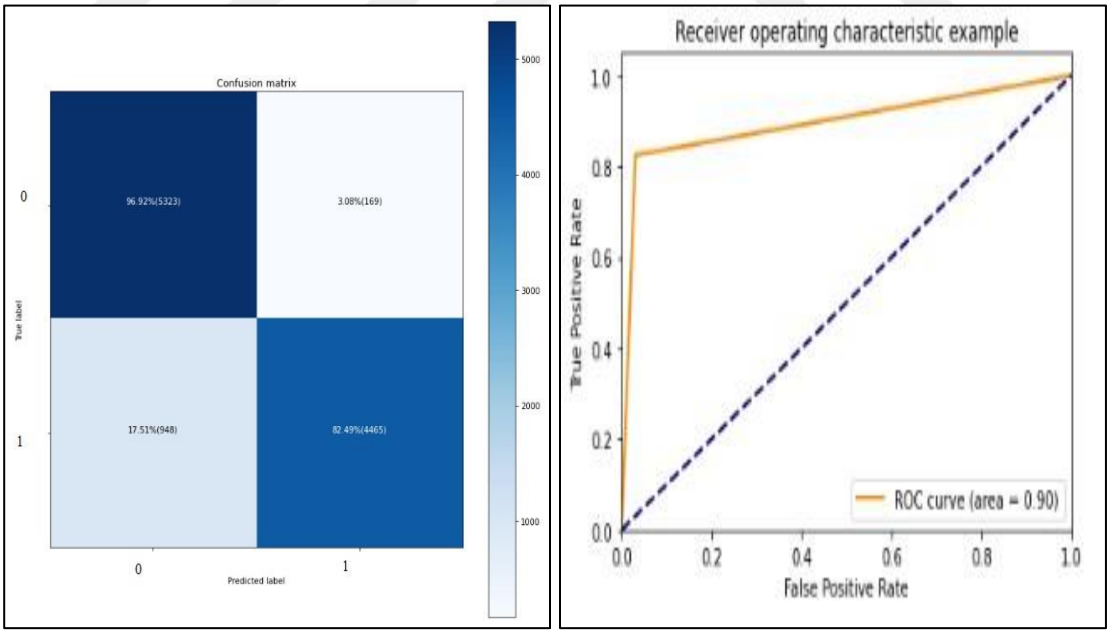
The results of the suggested technique are shown in Table 4.1. The framework of the research training and testing outcomes are presented in Table 4.3. To classify immigrant photos, we turned to several different CNN (convolutional neural network) models, including our own CNN approach, VGG16, VGG19, and InceptionV3. The DL model was evaluated using a variety of metrics, including area under the curve of the receiver operating characteristic (AUC ROC), precision, recall, accuracy, F1-scoring confusion matrix, and recall accuracy. The data was divided into three categories for further in-depth analysis: The remaining 30% was put to use verifying the precision of the trained models, while the remaining 10% was put to use evaluating the efficacy of the CNN models. The CNN model achieved 89.02 percent accuracy on the validation set. The results of the tests showed an accuracy of 90.02%, a recall of 89.05%, an F1-score of 89.00%, and an area under the receiver operating characteristic curve (AUC) of 89%. InceptionV3 was the most accurate model, with a success rate of 89.01%. The tests were quite similar to those used for the CNN model, with the difference that the model's accuracy was better.

4.1.1 Vgg16 Model Results

When compared against other DL models, the VGG19 model did not fare well. Precision, accuracy, recall, and F1 scores were respectively 72.04%, 71.05%, 71.06%, and 71.02%, yielding a ROC area under the curve (AUC) of 71%.



(a) Training and Validation accuracy of VGG16 model (b) Training and Validation accuracy of VGG16 model



(c) VGG16 model confusion matrix (d). The area under the curve (AUC) of the ROC curve for the VGG16 model

Figure 4.1: Results of Fine-Tuned VGG16 Model.

Overfitting was not prevented by using a dropout layer, even if the original compact layer had a high unit value. When compared to the other DL models, the VGG16 model had the highest levels of precision and precision of measurement (90.03% and 91.03%, accordingly). Table 4.2 displays the VGG16 model's categorization outcomes. Classification results show that our enhanced VGG16 model can effectively separate the two groups. In the classification report, we show the average accuracy, recall, and F1 score as weighted averages. These are precision and loss graphs for training and validating the VGG16 model. The VGG16 model's validation accuracy (Fig. 4.1b) and training loss (Fig. 4.1a) are displayed below.

In Figure 4.1c, we see the VGG16 model-specific confusion matrix. The utilization of a confusion matrix is an essential technique for assessing the performance of classification models, exemplified by the VGG16 model in this particular scenario. The provided information offers a comprehensive analysis of the model's performance by presenting the number of cases accurately and inaccurately identified for each class. The confusion matrix offered encompasses two distinct classifications, namely "refugee" and "not-refugee." The following is a guide on how to understand the given information:

True positives (TP) refer to occurrences that are categorized as belonging to the "refugee" class and are appropriately identified as such. Inside the matrix provided, there exists a total of 5,323 occurrences that can be classified inside this specific category.

False negatives (FN) refer to situations that are part of the "refugee" category but have been inaccurately labeled as "not-refugee." Within the matrix provided, there exists a total of 169 occurrences falling under this particular category.

True negatives (TN) refer to occurrences that are classified correctly as "not-refugee" and indeed belong to the "not-refugee" class. Within the matrix provided, it is observed that there exists a total of 4,465 occurrences falling under this specific category.

False positives, often known as FP, refer to instances that are categorized as the "refugee" class, despite actually belonging to the "not-refugee" class. Within the matrix provided, there exists a total of 948 occurrences falling under this specific category.

The value located in the top-left position (5323) corresponds to the TP, which denote occurrences that have been accurately identified as "refugee." The result located in the top-right position (169) corresponds to the FN in the classification task. False negatives refer to cases where the label "refugee" is erroneously predicted as "not-refugee." The value located in the bottom-left cell (948) corresponds to the category of FP, which denotes cases that are labeled as "refugee" when they should really be classified as "not-refugee." The value located in the bottom-right cell (4465) corresponds to the TN, which indicate the number of instances that have been accurately identified as "not-refugee." Based on the results of the tests, the VGG16 model seems to generate a confusion matrix with low levels of confusion. As an extra safety measure, we calculated the AUC for the VGG16 model. If the model's AUC is more than 85%, then the results make sense. The AUC of the ROC is shown in Fig. 3d. Receiver-operator-characteristic (ROC) graphic for the VGG16 model has an area under the contour (AUC) of 90%. The Fine-tuned VGG16 model has a higher accuracy (90%), in contrast to other machine learning models. Training duration for the recommended VGG-16 model, which uses transfer learning, was one hour. The suggested model requires an hour of processing time.

Table 4.1: Experimental Results of Various CNN Models.

Model	Accuracy	Precision	Recall	F1-Score	Roc Score
CNN	89.02%	90.02%	89.05%	89.03%	89%
VGG16	90.03%	91.03%	90.06%	90.01%	90%
InceptionV3	89.01%	91.01%	89.04%	89.04%	89%
VGG19	71.05%	72.04%	71.06%	71.02%	71%

Table 4.2: VGG16 Classification Report Table.

Class	precision	recall	f1-score	support
Refugee	0.85%	0.97%	0.91%	5492
Normal	0.96%	0.82%	0.89%	5413
accuracy	-	-	0.90%	10905
macro avg	0.91%	0.90%	0.90%	10905
weighted avg	0.91%	0.90%	0.90%	10905

Table 4.3: Training and Testing Results of CNN Models.

Model	Train	Test
CNN	95.78%	89.02%
VGG16	98.36%	90.03%
InceptionV3	97.58%	89.01%
VGG19	79.92%	71.05%

4.1.2 Cnn Model Results

The results presented above are derived from the assessment of a Convolutional Neural Network (CNN) model, encompassing a range of performance criteria. Let us proceed to analyze these parameters in a more comprehensive manner. The results of CNN model can be seen in Figure 4.2, Table 4.1 and 4.3.

The overall accuracy of the model.

Accuracy is a metric that quantifies the ratio of correctly classified cases to the total number of examples. In this particular instance, the model exhibits an accuracy rate of 89.02%. This implies that the model accurately classified around 89.02% of all cases.

Precision, also known as positive predictive value, refers to the proportion of true positive results among all positive results. Precision is a metric that quantifies the degree of accuracy in the positive predictions generated by a given model.

In the context of class 0, which is assumed to represent individuals who are not refugees, the precision value is determined to be 0.85. This implies that of all the occurrences that were classified as "not-refugee," 85% were correctly identified as "not-refugee" (true positives), whereas 15% were incorrectly classified as "refugee" (false positives).

In the context of the first class, which is likely designated as the "refugee" class, the precision value is recorded as 0.94. This data suggests that of all occurrences classified as "refugee," 94% were correctly identified as such (true positives), whereas 6% were incorrectly classified as "not-refugee" (false positives).

The recall, also known as sensitivity or true positive rate, refers to the proportion of true positive instances that are correctly identified by a classification model. The recall metric quantifies the ratio of accurately anticipated positive instances to the total number of actual positive instances.

In the context of the class under consideration, the recall metric is seen to be 0.95. This indicates that of all occurrences that were not categorized as refugees, the model accurately classified 95% of them as true negatives, while 5% were incorrectly classified as false negatives.

In the first class, the recall metric is 0.83. This finding suggests that among all observed instances of individuals labeled as "refugees," the model accurately identified 83% of them as true positives, while 17% were incorrectly classified as false negatives. The F1-Score, sometimes known as the F1-Measure, is a metric used to evaluate the performance of a

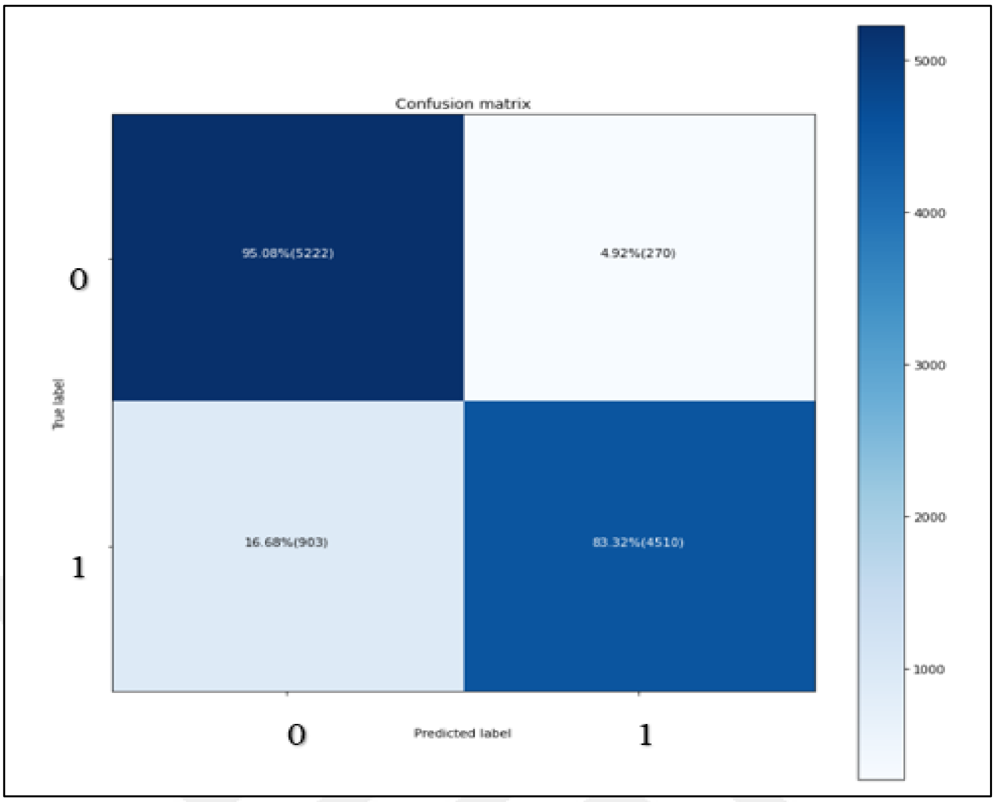
The F1-score can be defined as the mathematical average of precision and recall, specifically calculated using the harmonic mean. The aforementioned approach achieves a harmonious equilibrium between precision and recall. In the context of class 0, the F1-score is calculated to be 0.90, suggesting a harmonious equilibrium between precision and recall for the "not-refugee" category. In the context of class 1, the F1-score is calculated to be 0.88, which suggests a harmonious equilibrium between precision and recall for the specific class labeled as "refugee". The provided data indicates the number of instances that support the given argument. Support refers to the frequency or count of occurrences in each class. In the context of the course, it can be observed that class 0 comprises a total of 5,492 instances. In the first class, there are a total of 5,413 occurrences. The macro average refers to the arithmetic mean of a set of values or measurements. The macro average is computed by individually calculating the average of metrics like as precision, recall, and F1-score for each class, and afterwards determining the mean. In this instance, the macro average precision, recall, and F1-score exhibit values about equal to 0.90, suggesting a commendable equilibrium of performance metrics across both classes. The concept of a weighted average is a mathematical calculation that assigns different weights or importance to different values in order to obtain an overall average.

The weighted average is a statistical measure that computes the mean of various metrics, including as accuracy, recall, and F1-score, for individual classes. However, it incorporates the consideration of class imbalance by assigning weights proportional to the number of occurrences in each class.

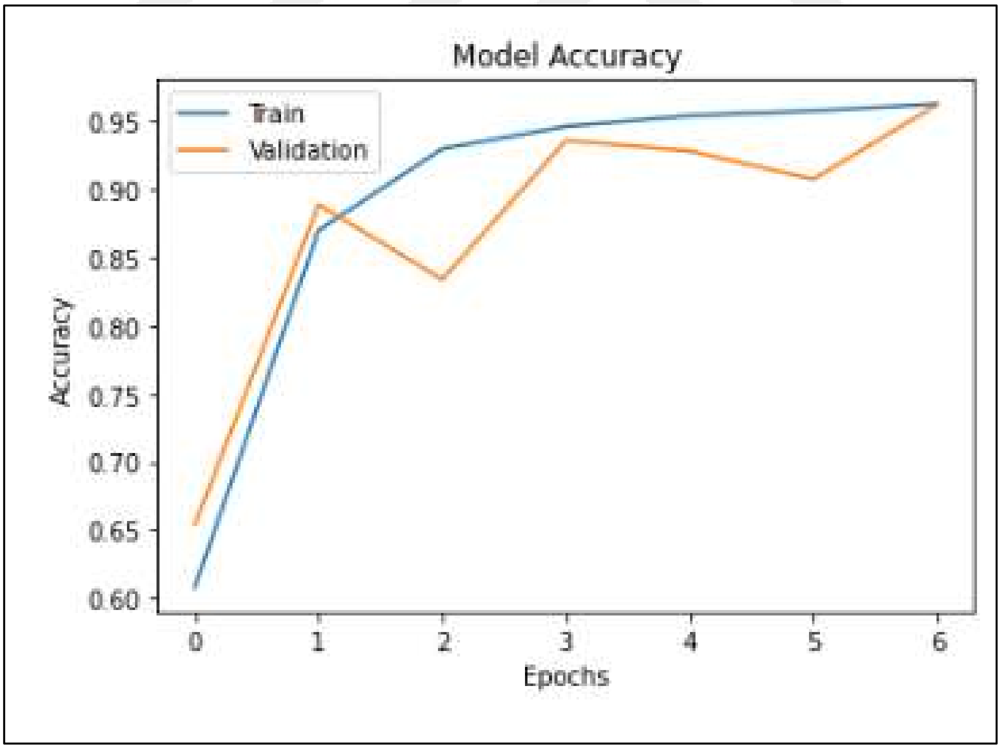
In this particular instance, the weighted average precision, recall, and F1-score exhibit values about equal to 0.90, so signifying a commendable overall performance when accounting for class imbalances.

In brief, the aforementioned findings offer a comprehensive perspective on the performance of the CNN model in the context of binary classification, namely distinguishing between the "not-refugee" category (class 0) and the "refugee" category (class 1). The model exhibits high levels of accuracy, precision, recall, and F1-score, suggesting its efficacy in accurately categorizing cases from both groups. Nevertheless, it is crucial to take into account the precise demands of the problem when evaluating these metrics, as the significance of precision or recall may vary depending on the individual application.

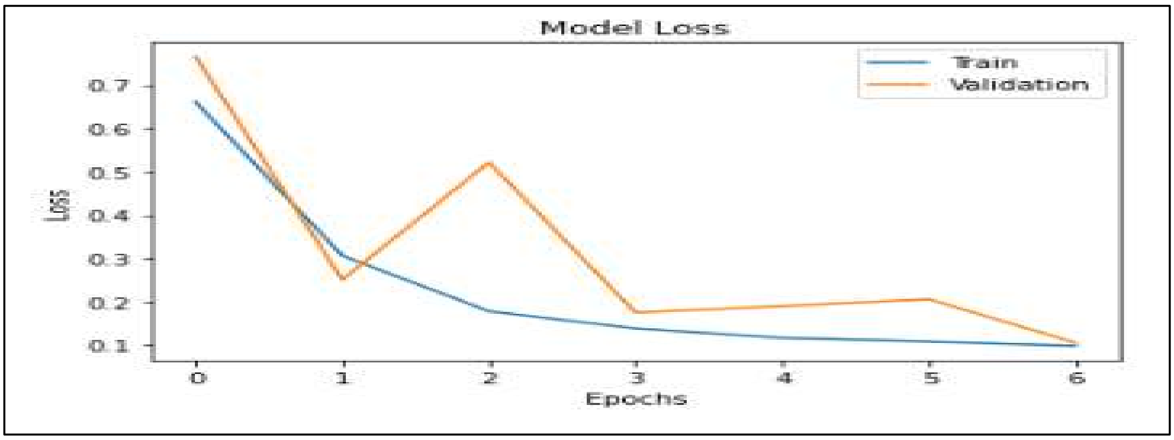
Figure 4.2 displays many performance metrics, including the confusion matrix, ROC curve score, and classification report, and training and validation accuracy and loss.

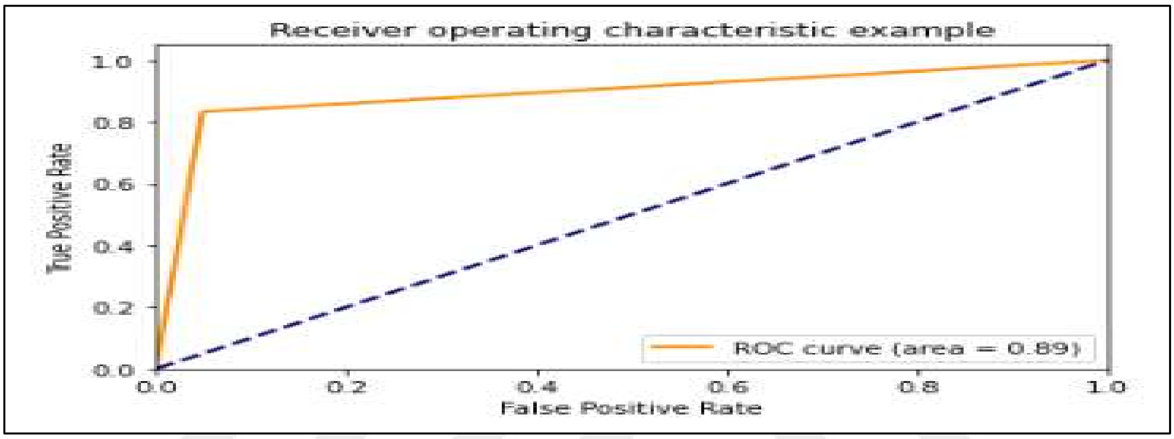


(a) CNN model confusion matrix



(b) Training and Validation accuracy of CNN model





(c) Training and Validation loss of CNN Model (d). The area under the curve (AUC)

	precision	recall	f1-score	support
0	0.85	0.95	0.90	5492
1	0.94	0.83	0.88	5413
accuracy			0.89	10905
macro avg	0.90	0.89	0.89	10905
weighted avg	0.90	0.89	0.89	10905

(e) Classification Report of CNN Model

Figure 4.2: Results of Fine-Tuned CNN Model.

According to Figure 4.2a, the utilization of a confusion matrix is imperative in the assessment of the efficacy of a classification model, namely the CNN in this particular instance. The provided analysis offers a comprehensive delineation of the model's predicted outcomes in relation to the observed classes. The confusion matrix supplied consists of two distinct classifications, namely "refugee" and "not-refugee." Let us now proceed to examine the intricacies and nuances of the subject matter at hand.

Within this matrix, there exist 5,222 occurrences that pertain to the "refugee" category, which have been accurately identified and classed as such. The aforementioned are the model's true positives, denoting cases that have been accurately classified as "refugee."

A total of 270 cases, which pertain to the "refugee" class, were erroneously classed as "not-refugee." The aforementioned occurrences represent the model's false negatives, indicating that the model failed to correctly identify them as "refugee."

TN refer to situations in which the "not-refugee" class is correctly categorized as such. In this case, there are 4,510 instances that have been accurately classified as "not-refugee." The aforementioned are the accurate negative classifications, denoting situations that have been appropriately designated as "not-refugee."

The number of occurrences erroneously classified as "refugee" when they actually belong to the "not-refugee" class is 903, thus resulting in false positives (FP). The aforementioned examples are classified as false positives, signifying that the model has erroneously labeled them as "refugee."

In essence, the confusion matrix provides a comprehensive perspective on the performance of the CNN model in the context of binary classification, namely distinguishing between the "refugee" and "not-refugee" classes. The model demonstrated a considerable number of true positives and true negatives, suggesting its ability to accurately classify a big proportion of occurrences. Nevertheless, it is worth noting that the model's performance exhibits instances of both false positives and false negatives, indicating the existence of areas that could benefit from enhancement, particularly in the mitigation of false positives and false negatives.

4.1.3 Inceptionv3 Model Results

The results presented in this section are derived from the assessment of an InceptionV3 model, encompassing a range of performance criteria. Let us proceed to analyze these parameters in a more comprehensive manner. The results are presented in Figure 4.3 and Table 4.1 and 4.3.

The overall model accuracy, also referred to as accuracy, is a measure of the correctness of predictions made by a model. The measure of accuracy quantifies the ratio of correctly classified examples to the total number of instances. In the present scenario, the model exhibits an accuracy rate of 89.01%. This indicates that the model achieved an accuracy rate of roughly 89.01% in accurately classifying cases. Precision, also known as positive predictive value, refers to the proportion of true positive results among all positive results. Precision is a metric that evaluates the correctness of positive predictions generated by a given model. In the context of class 0, which is assumed to represent individuals who are not refugees, the precision value is observed to be 0.84. This indicates that among all cases classified as "not-refugee," 84% were correctly identified as "not-refugee" (true positives), whereas 16% were incorrectly classified as "refugee" (false positives). In the context of the first class, which is likely focused on the topic of refugees, the precision value is reported as 0.98. This data suggests that of all cases classified as "refugee," 98% were correctly identified as such (true positives), whereas 2% were incorrectly labeled as "not-refugee" (false positives). The recall, also known as sensitivity or true positive rate, is a metric used to measure the proportion of true positive instances correctly identified by a classification model. The recall metric quantifies the ratio of accurately anticipated positive instances to the total number of actual positive instances.

In the context of the class being referred to as "class 0," the recall metric is reported to be 0.98. This implies that among all occurrences that were not classified as refugees, the model accurately identified 98% as true negatives, while 2% were incorrectly identified as false negatives. The recall for class 1 is 0.81 in the given context. This data suggests that the model accurately classified 81% of the observed cases as "refugee" (true positives), while 19% of the instances were incorrectly labeled as non-refugee (false negatives). The F1-score can be defined as the mathematical average of precision and recall, specifically calculated using the harmonic mean. The aforementioned approach achieves a harmonious equilibrium between precision and recall. In the context of class 0, the F1-score is seen to be 0.90, suggesting a harmonious equilibrium between precision and recall for the "not-refugee" category.

In the context of the first class, the F1-score is determined to be 0.88, signifying a harmonious equilibrium between precision and recall for the class labeled as "refugee." The provided data supports the argument by demonstrating the frequency or occurrence of a particular phenomenon. In the context of the course, there exists a total of 5,492 instances for class 0. In the first class, there are a total of 5,413 occurrences. The macro average refers to a statistical measure that calculates the average value over multiple categories or groups. It is commonly used in academic research

The macro average is computed by individually calculating the average of metrics like as precision, recall, and F1-score for each class, and afterwards determining the mean.

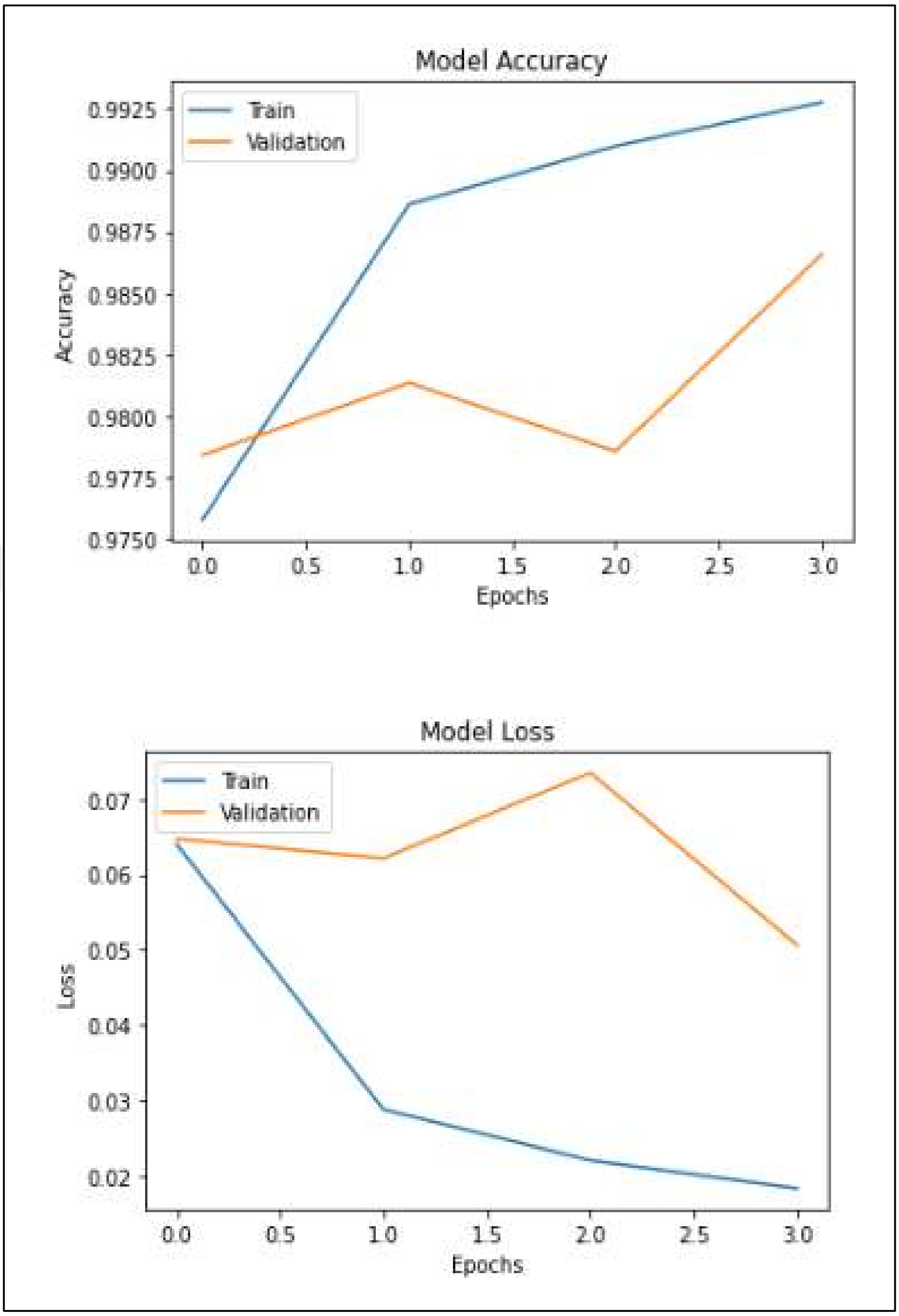
In this particular scenario, the macro average precision, recall, and F1-score exhibit values about equal to 0.91, suggesting a commendable equilibrium of performance metrics across both classes. The concept of weighted average refers to a mathematical calculation that takes into account the relative importance or significance of different values or data points.

The weighted average is a statistical measure that computes the mean of various metrics, such as accuracy, recall, and F1-score, for individual classes. However, it addresses the issue of class imbalance by assigning weights to each class based on the number of instances present in that class.

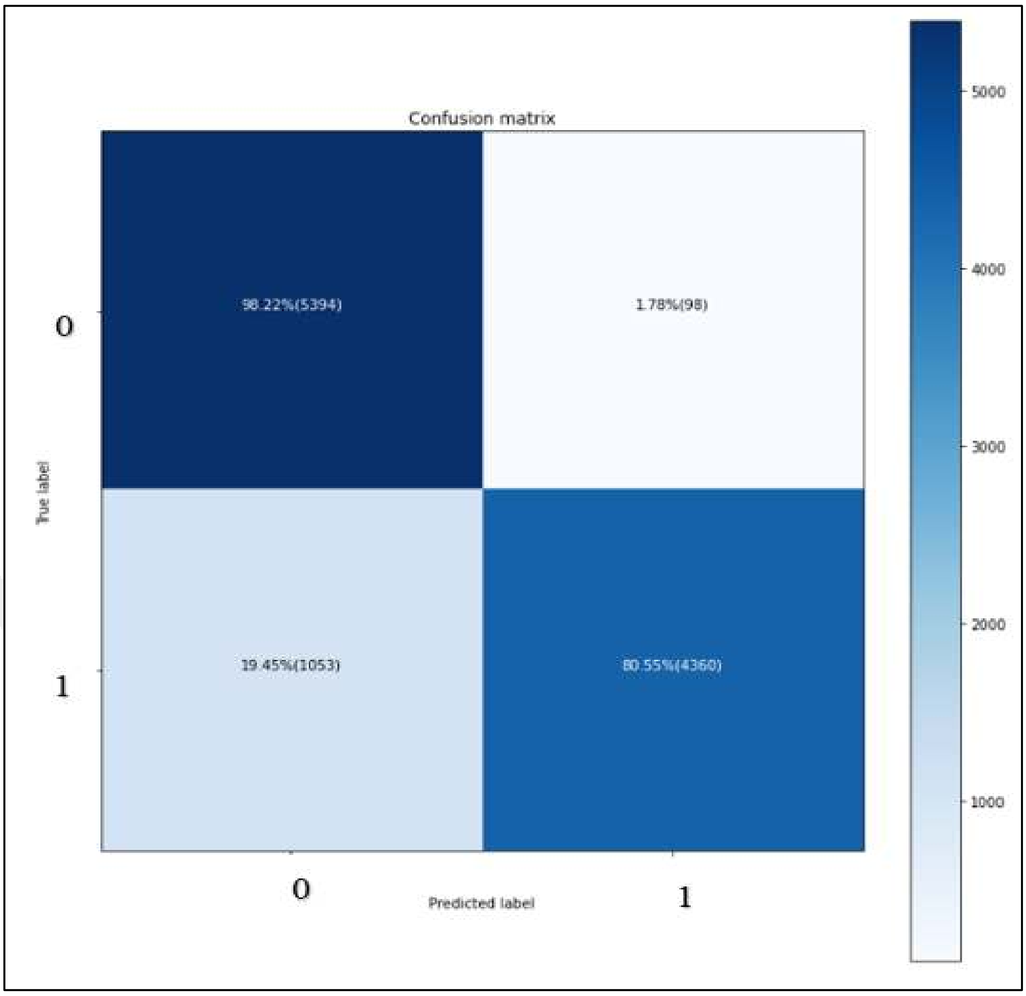
In this particular instance, the calculated weighted average precision, recall, and F1-score all approximate 0.91, suggesting a commendable overall performance when accounting for disparities in class distribution.

In conclusion, the aforementioned findings offer a comprehensive perspective on the performance of the InceptionV3 model in the context of binary classification, namely distinguishing between the "not-refugee" (class 0) and "refugee" (class 1) categories. The model exhibits strong performance in terms of overall accuracy, precision, recall, and F1-score, suggesting its efficacy in accurately identifying cases from both classes. The utilization of weighted average metrics takes into consideration the presence of imbalances among classes within the dataset.

Figure 4.3 displays many performance metrics, including the confusion matrix, ROC curve score, and classification report, and training and validation accuracy and loss.

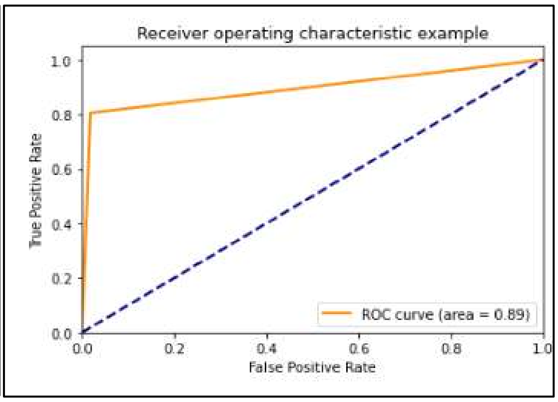


(a) Training and validation results of InceptionV3 Model



(b) Confusion matrix ofInceptionV3 Model

	precision	recall	f1-score	support
0	0.84	0.98	0.90	5492
1	0.98	0.81	0.88	5413
accuracy			0.89	10905
macro avg	0.91	0.89	0.89	10905
weighted avg	0.91	0.89	0.89	10905



(c) AUC Score of InceptionV3 Model (d) Classification Report of InceptionV3 Model

Figure 4.3: Results of Fine-Tuned InceptionV3 Model.

According to Figure 4.3b, the utilization of a confusion matrix is an essential methodology for evaluating the efficacy of a classification model, exemplified as InceptionV3. The matrix shown herein offers a comprehensive description of the model's predictions in relation to the actual classes. The confusion matrix supplied consists of two distinct classifications, namely "refugee" and "not-refugee." Let us now proceed to examine the intricacies and specifics of the subject matter at hand.

Within this matrix, there exists a total of 5,394 occurrences that pertain to the "refugee" category, which have been accurately identified and classed as such. The aforementioned are the model's accurate positive predictions, denoting occurrences that have been accurately classified as "refugee”. A total of 98 cases, which are part of the "refugee" class, were erroneously classed as "not-refugee." The aforementioned examples are classified as false negatives by the model, indicating that the model failed to correctly identify them as "refugee."

The number of cases correctly classified as "not-refugee" for the "not-refugee" class is 4,360, representing the TN. The true negatives refer to occurrences that have been accurately classified as "not-refugee."

The dataset contains 1,053 cases categorized as "not-refugee" that were erroneously identified as "refugee," resulting in FP. The aforementioned examples are classified as false positives, signifying that the model has erroneously labeled them as "refugee."

In essence, the confusion matrix provides a comprehensive evaluation of the performance of the InceptionV3 model in binary classification, namely distinguishing between the "refugee" and "not-refugee" classes. The model demonstrated a considerable quantity of true positives and true negatives, suggesting that it accurately identified a noteworthy proportion of occurrences. Nevertheless, it is worth noting that the model's performance exhibits instances of both false positives and false negatives, indicating the existence of areas that could benefit from enhancement. Specifically, mitigating the occurrence of false positives and false negatives emerges as a crucial feature warranting development.

4.1.4 Vgg19 Model Results

The results presented in Figure 4.4 are derived from the assessment of a VGG19 model, encompassing a range of performance criteria. In order to gain a deeper understanding of these measures, it is necessary to conduct a more comprehensive analysis and delve into the potential reasons behind the relatively low results obtained by the model.

The overall model accuracy, also referred to as accuracy, is a measure of the correctness of predictions made by a model. Accuracy is a metric that quantifies the ratio of accurately classified examples to the total number of instances. In the present scenario, the model exhibits an accuracy rate of 71.05%. This indicates that the model accurately classified around 71.05% of all cases.

The precision, also known as the positive predictive value, is a measure used in academic research to assess the accuracy of a predictive model or diagnostic test. Precision is a metric that evaluates the correctness of positive predictions generated by a given model.

In the context of the class denoted as 0, which is assumed to represent individuals who are not classified as refugees, the precision value is recorded as 0.68. This implies that among all cases classified as "not-refugee," 68% were correctly identified as "not-refugee" (true positives), whereas 32% were incorrectly classified as "refugee" (false positives). In the context of the first class, which is likely designated as the "refugee" class, the precision value is recorded as 0.76. This data demonstrates that of all occurrences classified as "refugee," 76% were correctly identified as such (true positives), whereas 24% were incorrectly classified as "refugee" when they were actually "not-refugee" (false positives).

The recall, also known as sensitivity or true positive rate, is a metric used to measure the proportion of true positive instances correctly identified by a classification model. The recall metric quantifies the ratio of accurately anticipated positive instances to the total number of actual positive instances.

In the context of the class being referred to as "class 0," the recall metric is reported to be 0.81. This indicates that of all occurrences labeled as "not-refugee," the model accurately identified 81% as genuine negatives, while 19% were incorrectly classified as false negatives. The recall value for class 1 is 0.61 in the given context. This finding suggests that among all observed instances of individuals classed as "refugees," the model accurately identified 61% of them as true positives, whereas 39% were incorrectly identified as false negatives.

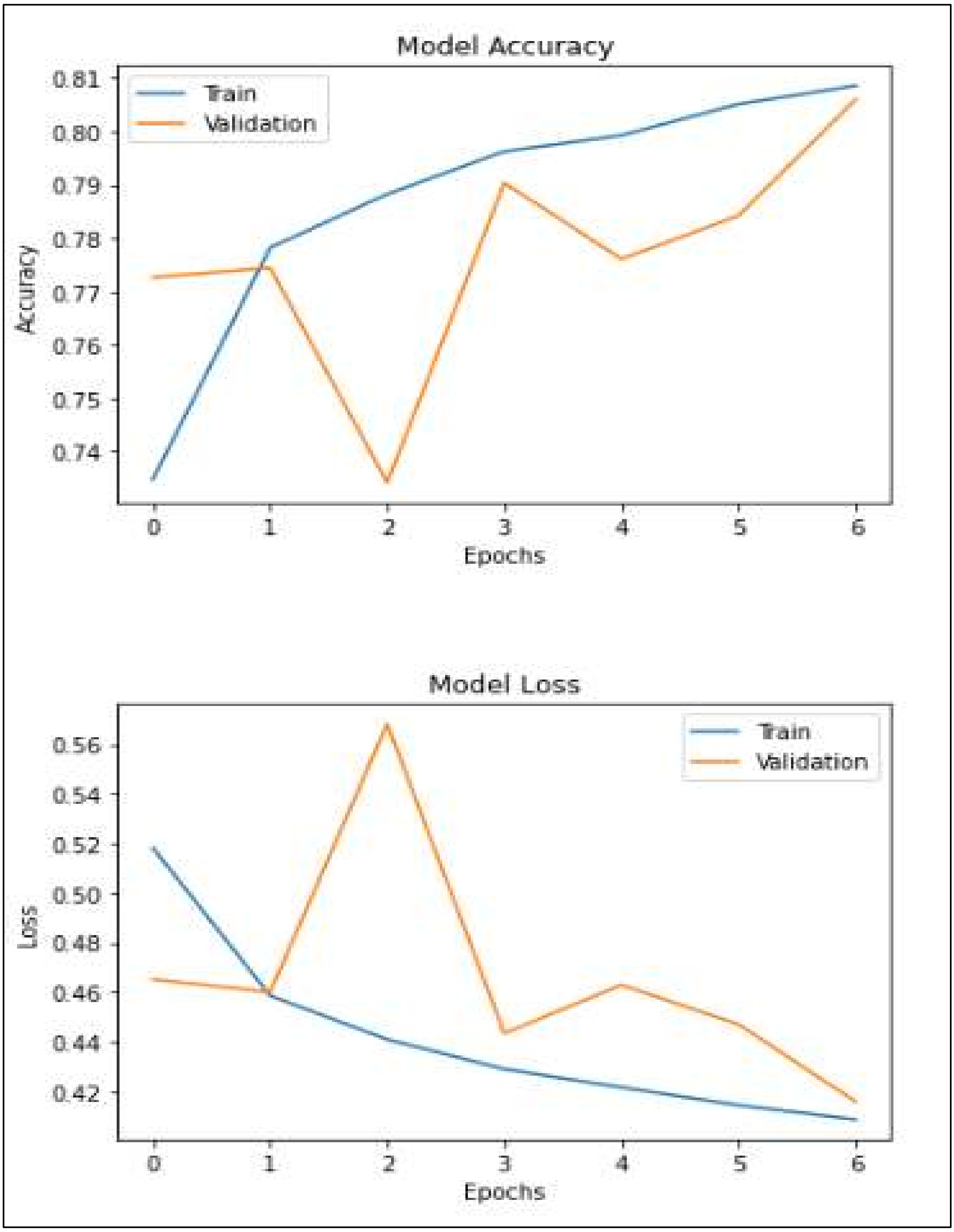
The F1-score can be defined as the mathematical average of precision and recall, specifically calculated using the harmonic mean. The aforementioned approach achieves a harmonious equilibrium between precision and recall. In the context of class 0, the F1-score is observed to be 0.74, suggesting a satisfactory equilibrium between precision and recall for the "not-refugee" category. In the context of class 1, the F1-score is calculated to be 0.67, suggesting a satisfactory equilibrium between precision and recall for the "refugee" category.

Support refers to the frequency or count of occurrences within each class. In the context of the course, it is observed that there are a total of 5,492 instances in class 0. In the first class, there are a total of 5,413 occurrences.

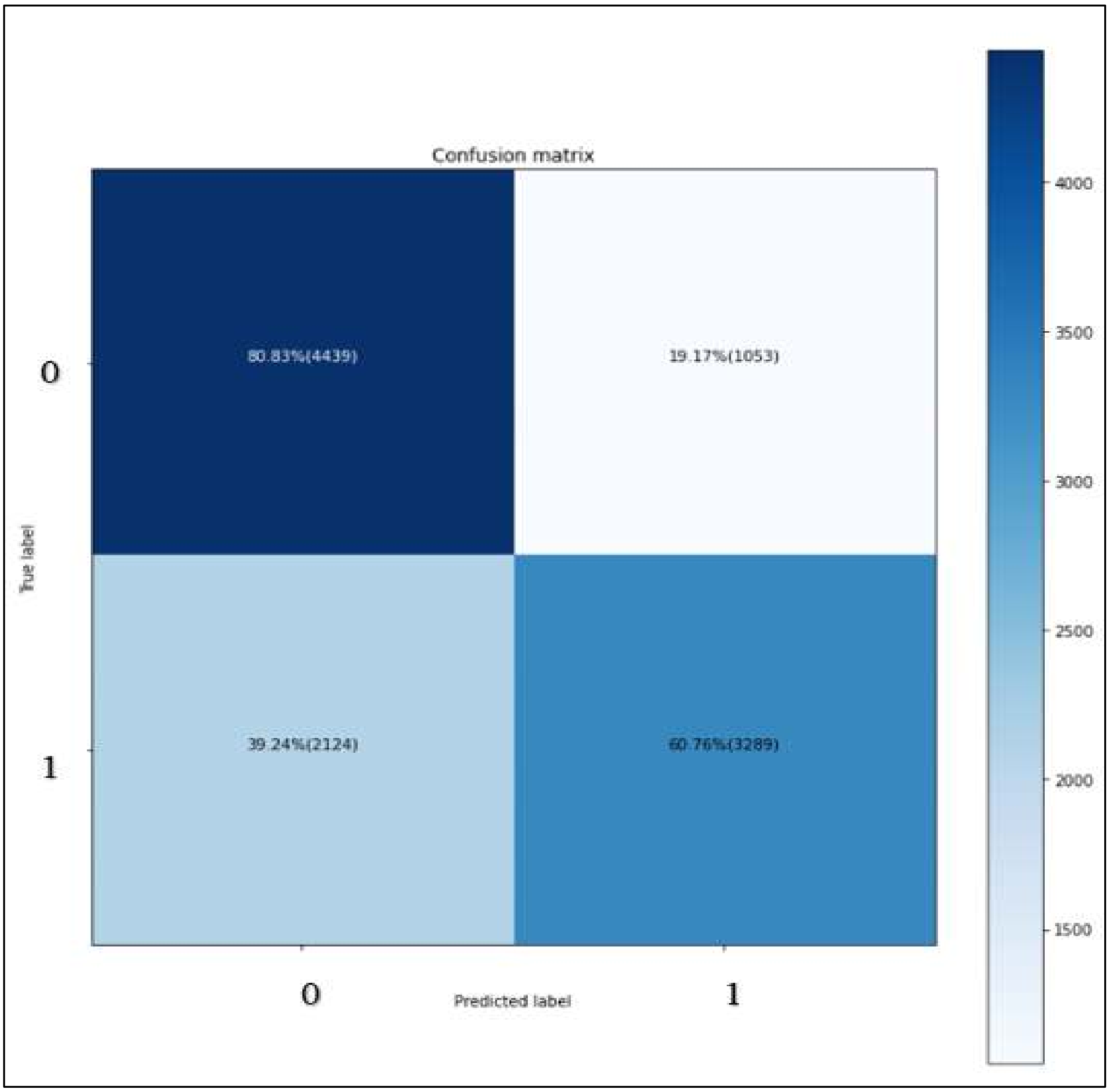
Now, let us proceed to examine the potential factors contributing to the comparatively low outcomes of the model. The dataset exhibits a very equitable distribution across the two groups, indicating a lack of significant class imbalance. Nevertheless, in the event of an asymmetry, the performance of the model may be impacted, particularly when one class exhibits a much lower number of cases. The task of image categorization, particularly when it involves making fine-grained distinctions such as differentiating between "refugee" and "not-refugee," might provide inherent complexities. The perceptual disparities between the two categories may not be readily discernible, resulting in diminished precision. The performance of the model can be influenced by the quality of the training data, which include labeling errors or noise. The VGG19 model is considered to be an earlier architecture in comparison to more contemporary models such as InceptionV3 or ResNet. The potential inadequacy of correctly capturing intricate details may lead to diminished performance. The selection of hyper parameters, including but not limited to the learning rate, batch size, and optimization technique, can have a substantial impact on the performance of the model. The optimization of these hyper parameters has the potential to enhance the obtained outcomes. The utilization of data augmentation methods, such as picture rotation, scaling, and flipping, has the potential to enhance the generalization of models and enhance their performance.

In order to enhance the performance of the model, it is advisable to explore various architectural designs, optimize hyper parameters, and improve the quality and diversity of the dataset. Moreover, the utilization of fine-tuning and transfer learning techniques from pre-existing models has been observed to yield advantages in the context of picture classification tasks.

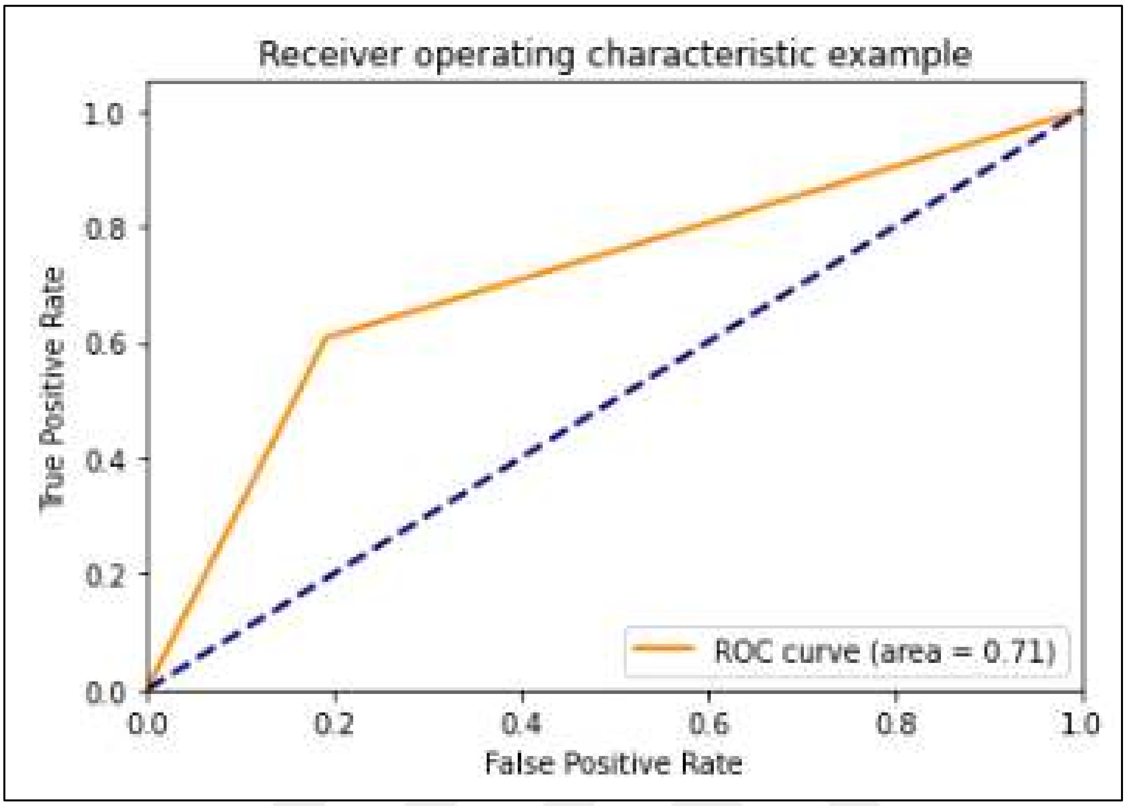
Figure 4.4 displays many performance metrics, including the confusion matrix, ROC curve score, and classification report, and training and validation accuracy and loss.



(a) Training and validation results of VGG19 Model



(b) Confusion matrix of VGG19 Model



(b)AUC Score of VGG19 Model

	precision	recall	f1-score	support
0	0.68	0.81	0.74	5492
1	0.76	0.61	0.67	5413
accuracy			0.71	10905
macro avg	0.72	0.71	0.71	10905
weighted avg	0.72	0.71	0.71	10905

(d) Classification Report of VGG19 Model

Figure 4.4: Results of Fine-Tuned VGG19 Model.

According to Figure 4.4b, the utilization of a confusion matrix is an essential technique for assessing the efficacy of a classification model, such as VGG19. The provided analysis offers a comprehensive examination of the extent to which the model's predictions correspond with the observed classes. The confusion matrix supplied contains two distinct groups, namely "refugee" and "not-refugee." The following is a comprehensive elucidation: The TP in the matrix consist of 4,439 instances that pertain to the "refugee" class and have been accurately identified as such. The aforementioned entities represent the instances correctly identified by the model as positive. A total of 1,053 cases, which pertain to the "refugee" class, were erroneously classed as "not-refugee." The aforementioned examples are classified as FN, indicating that the model failed to correctly identify them as "refugee." The number of cases correctly classified as "not-refugee" in the "not-refugee" class is 3,289, which represents the true negatives TN. The true negatives refer to incidents that have been accurately classified as "not-refugee."

The dataset contains 2,124 cases that were erroneously classified as "refugee" when they actually belong to the "not-refugee" class. These occurrences are referred to as FP. The occurrences tagged as "refugee" by the model are considered false positives, indicating that they were erroneously classified.

In summary, the confusion matrix offers a comprehensive perspective on the performance of the VGG19 model in binary classification, namely distinguishing between the "refugee" and "not-refugee" classes. The model demonstrated a substantial number of true positives and true negatives, suggesting that it accurately identified a noteworthy proportion of occurrences. Nevertheless, it is important to acknowledge the presence of significant instances of both false positives and false negatives, indicating the need for enhancements in specific facets of the model's efficacy, particularly in the mitigation of false positives and false negatives.

4.2 COMPARISON OF RESULTS

Figure 4.5 shows the deep learning model performance metrics for four different models: CNN, VGG16, Inception V3, and VGG19. These measurements include precision, recall, and F1-score.

Among these models, VGG16 comes out on top in terms of accuracy, with a whopping 90.03%. It also has a high precision rate of 91.03% and a high recall rate of 90.06%, resulting in an F1-score of 90.01%. VGG16 is the best performer in the evaluation based on these measures.

VGG19, on the other hand, has the lowest performance of the models. It has a 71.05% accuracy rate, a precision rate of 72.04%, a recall rate of 71.06%, and an F1-score of 71.02%. According to these criteria, VGG19 has the lowest accuracy and precision, making it the least effective model in the evaluation.

In comparison to the prior system, VGG16 and Inception V3 clearly outperform it in terms of accuracy, precision, recall, and F1-score. Both models have higher accuracy and precision rates, showing a stronger ability to identify and predict events. VGG19, on the other hand, while exhibiting lesser accuracy and precision than the prior system, falls behind in terms of performance.

Finally, VGG16 emerges as the best-performing model, with the highest accuracy and precision among the tested models. VGG19, on the other hand, trails behind, registering the lowest performance metrics. When compared to the prior system, VGG16 and Inception V3 show significant improvements in overall performance, highlighting its potential for use in real-world applications.

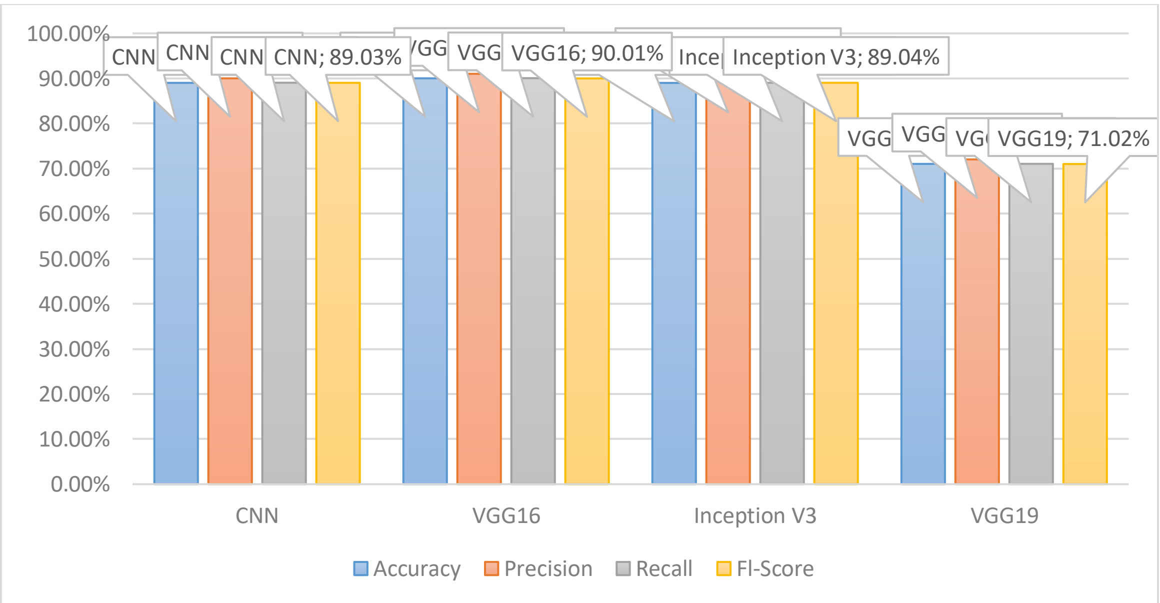


Figure 4.5: Results of Deep Learning Model.

4.3 COMPARISON WITH EXISTING STUDY

In the context of this research, it is worth noting that there has been little earlier work especially focused on the detection of refugees in Turkey using Artificial Intelligence (AI). Given the narrow scope of this topic, this study conducted a comparative analysis. It aimed to glean insights and approaches from a related study conducted in 2023 by Amram et al. While their study was unique in its subject matter, it used artificial intelligence to detect and diagnose depression among refugees in chosen diasporic literature. This contrast enabled us to use their AI-based method as a model and source of inspiration for addressing the unique issues of refugee tracking and identification in the Turkish setting. This study aims to pave the road for the innovative use of AI in refugee management and humanitarian operations in Turkey by adapting and expanding on their findings.

The Table 4.4 compares the proposed and existing approaches, concentrating on the accuracy and F1-Score metrics. The comparison sheds light on the significant improvements obtained by the proposed approach, and we will delve into the causes for these outcomes as well as the critical insights garnered.

The accuracy and F1-Scores of the suggested approach, which employs Convolutional Neural Networks (CNN), VGG16, and InceptionV3 models, are exceptional. The CNN model has an accuracy of 89.02% and an F1-Score of 89.03%, whereas the VGG16 model has an accuracy of 90.03% and an F1-Score of 90.01%. InceptionV3 retains its excellent level of performance, with an accuracy of 89.01% and an F1-Score of 89.04%. These outstanding results can be credited to deep learning models' capacity to grasp complicated patterns and characteristics in data, which makes them well-suited for the task.

On the other hand, the current technique, which employs models such as Naive Bayes (NB), Decision Trees (DT), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), produces much lower accuracy and F1-Scores. These models have accuracy scores ranging from 45% to 68% and F1-Scores ranging from 37% to 68%, demonstrating low efficacy in recognizing refugees in the proposed setting.

The proposed approach's strong results can be due to the ability of deep learning models, specifically VGG16, to extract complex features from data, allowing for precise categorization. These models excel at managing complicated and diverse datasets, such as refugee identification datasets. The proposed approach's resilience suggests that AI-based technologies, particularly deep learning, can be useful in tackling this real-world situation. This comparison revealed a key insight: when handling refugee identification problems, powerful AI and deep learning approaches must be used. Traditional machine learning models, as demonstrated in the current technique, perform poorly in comparison to deep learning models. This emphasizes the importance of implementing cutting-edge technology to improve the accuracy and efficacy of refugee management systems. It also emphasizes the potential for artificial intelligence to play a critical role in humanitarian endeavors, particularly in scenarios involving vulnerable populations such as refugees.

Table 4.4: Comparison of Proposed and Existing Research Results.

Model	Accuracy	F1-Score
Proposed Approach Results		
CNN	89.02%	89.03%
VGG16	90.03%	90.01%
InceptionV3	89.01%	89.04%
VGG19	71.05%	71.02%
Existing Approach Results [101]		
NB	68%	68%
DT	47%	45%
SVM	47%	43%
KNN	45%	37%

5. CONCLUSION, LIMITATIONS AND FUTURE WORK

5.1 CONCLUSION

Any displaced person who wants to leave the country will do so unethically, thus some system must be in place to track them. Our findings suggest that the AI-based approach may be useful for spotting undocumented individuals in public. Border patrol agents take photos and fingerprints of refugees and enter that information into a Sqlite3 database.

The refugees receive a software link by mobile SMS, and then use this to enter their personal information once and for all into the system. Convolutional neural networks are used to identify refugees. CNN models are trained on the refugee photo archive. The trained model was applied to all cameras, regardless of where they were placed. If a displaced person hasn't been seen for ten days, an alert will be sent every time they utilize the system or mode of transportation they were using. When migrants go missing, a camera will notify security, who will then use an artificial intelligence model to quickly identify them and take appropriate action. An open-source code web framework has been used for creating websites. The web-based framework in this research was developed using Flask and uses a Sqlite3 database to keep track of information. To teach the AI model, Python and an Nvidia GPU were employed. Binary classification was employed for model training. We have shifted our attention away from evaluation tools in favor of establishing a plan to help identify refugees in public and track down an elusive refugee who has fled the country illegally. Because we had so much information, our findings were only middling. Improving the AI-detection model calls for a sizable amount of high-quality data and a solid "feature engineering" strategy. Furthermore, a deep-fake detection system should be built by studying real-world refugees' appearance changes in images. We now have a whole system for tracking the migrants, but we haven't had enough to test it on all of the the municipality's security cameras.

In this research, the CNN model was used in four very important contexts: CNN, VGG16, and 2 more models. The transfer-learning-based VGG16 model fared better than its CNN predecessors. No studies to yet have used AI to track out displaced people. This study examines the results of different iterations of a CNN model used to detect refugees because of this problem. The study highlights the lack of previous research on using AI to identify migrants, highlighting the uniqueness of the proposed technique. To further understand the efficacy of alternative approaches, it is useful to compare the outcomes of several iterations of CNN models used to identify refugees. This can serve as a benchmark for future studies and as an illustration regarding the possibility of employing AI to track and identify refugees. The method used and the resulting data have an opportunity to contribute to the development of machine learning and relief efforts by facilitating the rapid and automatic detection of refugees in need of aid. More research is needed to prove the approach's efficacy and to address any ethical concerns.

The goal of this research is to find out ways to monitor the whereabouts of refugees in real time and notify authorities. A refugee in a public area can be found without the need for human intervention thanks to AI-based technology. We aren't putting in the effort necessary to improve our evaluation procedures and so provide improved outcomes. Rather, we're developing a method to locate and account for refugees. Once the displaced person has been discovered, the system will request that they provide an updated location. If they haven't done so in a while, the system will send them a text message asking them to confirm their current location. The suggested technology will alert authorities and send a text message to the refugees reminding them to update their whereabouts if they leave the country. The authorities and the armed forces will move swiftly to stop the refugees. For legal reasons, refugees are not permitted to exit the nation. Our long-term goal is to amass a larger sample size and optimize our use of feature engineering. This will improve the effectiveness of the AI model. We also use indentation to spot the deep-fake pictures. We'll also tweak our approach, so it works with every city camera.

5.2 LIMITATIONS

The research lacks a sufficient amount of high-quality data, which affects the efficacy of the AI-detection model. It was not possible to test the system on all of the municipality's security cameras. It is suggested, but not realized, to build a detecting system based on real-world refugee appearance changes in photographs.

5.3 FUTURE WORK

The future work will try to improve the system's effectiveness in locating and accounting for refugees by optimizing the evaluation procedures. To improve the AI model's performance, efforts will be made to increase the sample size and improve feature engineering. For improved picture analysis, the development and testing of a deep-fake image detecting system is being proposed. The goal is to perfect the method so that it works flawlessly with security cameras in every city.

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