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OPTIMIZING NETWORK PERFORMANCE ROUGH IMAGE PROCESSING TECHNIQUES IN OMPUTER SCIENCE IT

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Master's Thesis

Supervisor

Assoc. Prof. Dr. Sefer KURNAZ

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The thesis titled OPTIMIZING NETWORK PERFORMANCE THROUGH IMAGE PROCESSING TECHNIQUES IN COMPUTER SCIENCE IT prepared by HUSAM AMEER ABD ALMAGED AL KHAWAJA and submitted on 23/05/2025 has been **accepted unanimously** for the degree of Master of Science in Information Technologies.

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ABSTRACT

OPTIMIZING NETWORK PERFORMANCE ROUGH IMAGE PROCESSING TECHNIQUES IN OMPUTER SCIENCE IT

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A fundamental apparatus for exploring digital protection risks in Internet of Things (IoT) networks is the Botnet of Things (BoT-IoT) dataset. This examination proposes an original way to deal with order BoT-IoT information by changing over the crude information into RGB images and afterward applying calculations, for example, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Irregular Woodland to a helpful classification model. The BoT-IoT dataset is at first changed over into RGB images, where each component vector addresses a pixel in the image. To protect the spatial data of the first information, these photographs are in this manner saved in the.png design. We might take benefit of the strong capacities of example acknowledgment and image regulation procedures for IoT information examination with this change interaction. The RGB images delivered from the BoT-IoT dataset were then sorted utilizing an aggregate classification method. The ensemble includes the most striking Irregular Woodland classifiers, KNN, and SVM, every one of which contributes unmistakable qualities to the general classification issue. To show up at the last classification choice, the estimates of discrete classifiers are shared utilizing a weighted democratic system. The recommended strategy is compelling, as proven by trial discoveries on the BoT-IoT dataset, where the ensemble model accomplishes a great exactness of generally 99.36%. What's more, the model performs well with regards to precision, review, and F1-score, exhibiting its adequacy in isolating noxious action from harmless movement in Internet of Things networks. Inside and out review was likewise finished to explain every classifier's commitment inside the ensemble setting. This

examination uncovers the fitting properties of the classifiers: Arbitrary Timberland consolidates the limit of ensemble learning for upgraded speculation, KNN makes utilization of nearby neighbourhood data, and SVM succeeds at dealing with testing choice limits. In any case, this work offers a new way to deal with BoT-IoT information recording using ensemble learning strategies and RGB image models. The extraordinary exactness achieved features this strategy's capability to improve digital protection in Internet of Things networks. Through effective distinguishing proof and alleviation of pernicious activities, the proposed approach adds to the advancement of IoT security exploration and safeguards networked frameworks from arising digital threats.

Keywords: BOT-Iot Dataset, GB Image Representation, Ensemble Classification Model, Cybersecurity Threats, Iot Networks.

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ABBREVATIONS

CNN	:	Convolutional Neural Network
DL	:	Deep Learning
DOS	:	Denial of Service
DT	:	Decision Tree
FN	:	False Negative
FP	:	False Positive
IDS	:	Intrusion Detection System
KNN	:	K-Nearest Neighbor
LSTM	:	Long Short Term Memory
ML	:	Machine learning
MLP	:	Multilayer Perceptron
NB	:	Naïve Bayes
R2L	:	Remote to Local
RF	:	Random Forest
RNN	:	Recurrent Neural Network
SVM	:	Support Vector machine
TN	:	True Negative
TP	:	True Positive
U2R	:	User to Root

1. INTRODUCTION

1.1 BACKGROUND

The world's dependence on the Internet and its connected administrations has obviously expanded as of late. It isn't is business as usual that developments that take utilization of the Internet's interconnection will sometime become fundamental parts of day to day existence. Because of numerous advancements and devices meeting up, the Internet of Things (IoT) arose after the "universal figuring" time. The Internet of Things is one illustration of an advancement that has experienced critical development, according to Yang [1]. Digital actual frameworks are Internet of Things frameworks that incorporate networking, actuators, sensors, and computational power coordinated into them. According to concentrate by Shi and Sun, which was distributed in 2020, this method is valuable in various modern regions, including horticulture, water, power, and medical services. Furthermore, it makes it conceivable to offer an expansive scope of administrations by setting up exact and efficient robotized processes. The Internet of Things (IoT) is vital for both business and scholastic foundations.

The utilization of Internet of Things gadgets has flooded in the beyond quite a while. According to current appraisals, there were seven billion gadgets online at some random time in 2018. Munir [2] projects that by 2020, the above showed sum will have expanded to 20.4 billion. Introducing brilliant home apparatuses made up the bulk of Internet of Things organizations in 2017. These included carport doors, refrigerators, forced air systems, lighting, and machines. These establishments remembered very nearly 663 million units for complete. The Internet of Things (IoT) is comprised of continually fueled gadgets that trade information and commands across a remote network. According to Sparkle [3], things in an Internet of Things network can speak with each other through a cycle known as "thing-to-thing correspondence." Then again, items can speak with each other through an interaction known as "thing-to-cloud correspondence." In this situation, each gadget sends sensor information to the backend cloud framework, which gets it and sends commands back. Albeit these gadgets enjoy a few benefits, for example, incorporated command over geologically dispersed actuators and the improvement of business operations, they are likewise regularly the objective of cyberattacks because of their weak design. In 2018, Symantec delivered an

exploration named Hajiheidari [4] that portrays the recurrence of attacks on Internet of Things gadgets that have been reported, which surpasses 57,000. The exploration proceeds to express that there are 5,000 recorded attacks on normal consistently. Electronic gadgets associated with the Internet of Things are typically worked with compelled registering and power limits. Often, these devices are intended to be portable, set in places without electrical plugs, or designed to run simply during explicit hours of the day.

Furthermore, studies directed by Fahim [5] and Costa [6] have shown that a sizable percentage of Internet of Things (IoT) gadgets had serious security imperfections that should have been fixed immediately. Since to the "consistently dynamic" plan and the sending of inadequate safety efforts, the quantity of interruptions that take benefit of the Internet of Things for additional profit has expanded. A few instances of these attacks incorporate gigantic dispersed disavowal of administration attacks, which can think twice about Internet sectors and can arrive at rates of many gigabits per second (Gbps) or terabits per second (Tbps). The utilization of compromised Internet of Things gadgets to break security subnetworks Wang [9] and the abuse of digital actual frameworks, which permits hoodlums admittance to limited areas [7] [8]. Considering these circumstances, the proceeded with threats and weaknesses connected with the Internet of Things make the improvement of advanced forensic techniques an undeniably important task.

Reconnaissance and interruption identification research projects have fundamentally centered around supervised learning classification models. The Long Short-Term Memory (LSTM) [10], Convolutional Neural Network (CNN) [11], Support Vector Machine (SVM) [12], Deep Neural Network (DNN) [13], and Artificial Neural Network (ANN) [14] are a few instances of such plans. The Internet of Things is heterogeneous on the grounds that there are no plan and execution standards; this is shown by the way that various conventions and advances habitually coincide in a solitary framework. Making computerized forensic projects that work across an extensive variety of Internet of Things platforms is testing. Various tasks are remembered for the field of computerized forensics, like the extraction, protection, assessment, examination, and show of advanced proof that has been gathered from the shadowy internet domain [15]. These methods use strategies that have been supported by research from science. The field of computerized forensics needs expand into various subfields, like network, cloud, portable, and Internet of Things (IoT) forensics, to

keep up with the quick development of innovation [16][17]. Since most Internet of Things executions utilize the TCP/IP convention suite to interface with the backend cloud platform, network forensics can be utilized to assess security weaknesses without going into the complexities and heterogeneities of the circumstance. Notwithstanding the improvement of numerous network forensic frameworks, a large portion of them [18] [19] [20] [21] [22] center around the Internet of Things (IoT) obtaining stage. Along these lines, a thorough framework for network forensics is required, and its methodology ought to incorporate the phases of assessment and investigation.

1.2 RESEARCH MOTIVATION

According to Xu [23], the Internet of Things (IoT) is quickly turning into a crucial part of present day culture and an innovatively developed worldwide climate. Taking into account how quickly innovation is creating all through the world, this is particularly obvious. Because of the developing utilization of PCs and microsensors in day to day existence, brilliant gadgets are turning out to be more and more typical in current culture. Therefore, the omnipresent incorporation of processors and microsensors into ordinary exercises can be credited with this outcome. These capacities can give a huge range of helpful gadgets that can be utilized in various settings when joined with distributed computing and further developed artificial knowledge strategies. Accordingly, by joining these capacities with distributed computing and likewise further developing artificial insight algorithms, this fairness may be effectively understood. Furthermore, because of progressions in digitalization and, more importantly, association, the Internet of Things (IoT) has arisen as an undeniably worthwhile streamlining device for various cases. These applications incorporate, in addition to other things, asset the executives, transportation, and medical care. Internet of Things (IoT) based performance improvement for a large number of utilizations is turning out to be more and more famous and valuable. Notwithstanding other mechanical headways, the poliferation of association and digitization lately has fundamentally helped with the development of the Internet of Things (IoT) in terms of its importance and reality.

1.3 TYPES OF CYBER CRIME

According to Peng [24], security is a framework's capacity to keep up with the core upsides of the Confidentiality, Integrity, and Availability (CIA) trinity. Each CIA standard spotlights

on a specific part of a framework. Although the standard of mystery expresses that information should be kept hidden from unauthorized access, the guideline of integrity demands that information cannot be changed or erased. When information is available, it truly intends that there are no obstructions keeping clients from getting to the information. Cybercriminals can break the CIA group of three and rout the security and network of an Internet of Things framework in the event that they are totally ready. The acquisition of information stored on an Internet of Things-connected gadget through infiltration is a fundamental illustration of the objective that could rouse an attack. Nevertheless, more complicated plans involve involving the hacked gadget as a launchpad to launch attacks against more gadgets linked to the network. As a result of the huge swath of operations that they can perform, botnets are acknowledged as the most conspicuous and harming sort of threat that exists on the Internet.

Put in an unexpected way, botnets are gatherings of tainted gadgets heavily influenced by vindictive individuals called "botmasters." According to Kriegel [25], they can spread malware, take characters, exfiltrate information, send spam messages, keylog, and launch distributed denial of service (DDoS) and distributed denial of service attacks (DDoS). Although personal computers, workstations, and servers were the primary focuses of botmasters, another generation of botnets in light of the Internet of Things (IoT) has surfaced. This change in emphasis is brought about by the IoT gadgets' continuous communication and deficient safety efforts. According to Sinclair [26], botnets that make utilization of the Internet of Things (IoT) have expanded their attack toolkit to incorporate methods like bricking and Sybil attacks, which are particularly compelling against IoT gadgets. According to Zhang [27], a remarkable explosion of botnets from this new variety showed up in 2017 and 2018, wreaking havoc on Internet of Things gadgets and in any event, taking down whole spaces on their own.After being found for the initial time in 2016, Internet of Things (IoT) botnets — among which Mirai is one — have filled essentially in number [28].

With a peak throughput of 1.1 TBPS, Mirai's coordinated distributed denial of service (DDoS) attacks against On Vous Héberge (OVH), a French cloud service supplier, broke every past record. These attacks happened at the zenith of Mirai's expected power. Notwithstanding having a moderately straightforward framework, Mirai had the option to

do attacks and contaminate intermediaries very well. Thus, progressively complex botnets, such as Malware-Must Die, were made. These botnets utilized encryption modules that permitted the Command and Control (C&C) frameworks to speak with one another. Utilizing a zero-day weakness, the Persirai variation of Mirai, which was found in April 2017, tainted up to 120,000 devices [28].

Hajime involved public-private key encryption in a distributed command and control architecture to guarantee the protection of all conversations. Utilizing the default SSH passwords, the particularly hazardous botnet known as Bricker Bot sought to permanently deactivate any Internet of Things gadgets that were compromised. Aside from the traditional botnet attacks, Internet of Things-based botnets can complete many new attacks that influence digital physical frameworks. Bricking is an illustration of this sort of attack, which is otherwise called a persistent denial-of-service attack. Bricking is the method involved with changing the firmware of an Internet of Things gadget to make it unusable. Zhao [29] has distinguished a few procedures for malware propagation, one of which is the utilization of nearness infection. Through common infection amongst Internet of Things gadgets that are physically close to each other, the malware parallel can spread from a solitary Internet of Things gadget to a whole structure, or even a whole city.

Eventually, hackers have the capacity to influence real conditions. Hackers can be outfitted with a great many skills, such as the capacity to change sensor information, turn on and off electronic gadgets, and even find and follow a casualty. In brilliant houses, these abilities could be utilized to help perpetrate physical wrongdoings like thefts and break-ins [30] [31]. It is feasible to use each of these limits completely. The peril that cyberattacks present is only going to get greater. In a 2019 article, Zhong [32] reported that north of 18 million fake logins happened in the US somewhere in the range of 2017 and 2019. 5,000,000 came from Russia, while well more than three million came from Brazil. In the initial three fourth of 2018, more than 100,000 new instances of malware in view of the Internet of Things were found, according to a McAfee examination [33]. Thus, there is a strong push to give successful network forensic devices that are particularly made for botnet investigation in Internet of Things-related situations.

1.4 PROBLEM STATEMENT

One of the greatest challenges with network communication is the identification of infiltration crusades. While Ada boost, Innocent Bayes, Calculated Regression, and Decision Tree are machine learning-based intrusion detection models that achieve better exactness, it is important to perceive that these models additionally have a few major shortcomings. Making a dataset for a tweaked incident detection system (IDS) is a costly and tedious operation. The majority of the models perform severely when fitting pre-handling techniques are not utilized. These methodologies incorporate normalization, anomaly detection, and missing variable administration, among other comparable techniques. In the fields of machine learning and information science, highlights extraction is the most common way of distinguishing designs in the information that were recently hidden. It is achievable to decrease the highlights vector's dimensions by utilizing the elements selection technique. With this approach, the main characteristics are held while the superfluous ones are taken out. In the event that a short dataset (with under a thousand characteristics) is utilized, the cycle used to choose the elements for the dataset may have an impact on how well the model performed. To further develop network security and lessen the ability hole between the current intrusion detection system and the requirements of the network, an intrusion detection system in light of machine learning or deep learning must continuously outperform all attack classes.

1.5 OBJECTIVE

To design a bagging-based Classifier based Intrusion Detection System for IoT using Random Forest, K-Nearest Neighbour and Support Vector Machine.

To select the best features using evolutionary search algorithm to reduce features vector size and enhance the model training and validation efficiency.

To evaluate the performance of the proposed bagging Classifier based Intrusion Detection System for IoT in terms of accuracy with DNN, ANN, LSTM based CNN.

1.6 RESEARCH SIGNIFICANCE

The expanding importance of the internet and PC networks as of late has matched with the growth of safety as a significant component that requires attention. The status quo now has emerged from the expanded importance that is put on PCs and PC networks. In particular, as communicated in an undated blog passage named "Why Do outNeed Network Security?" from East Coast Polytechnic College. No PC network is totally protected from attacks, thus having a compelling network security system is vital for keeping it safe ("Why Do We Really want Network Security?" [unpublished blog post]). This category incorporates technologies like Intrusion Detection Systems (IDS), which are network security solutions intended to continuously examine PC systems for indicators of compromised integrity and cyberattacks. There are innumerable other technologies that fall under this heading. Systemic intrusion detection systems, or SIDS, should be introduced and are required. Network intrusion detection systems, or IDS for short, are intended to recognize and report harmful exercises happening within PC networks. One important advantage is that they make it more straightforward for network directors to counterattack by turning on safeguarding efforts quickly. Hackers' intelligence has expanded in sync with technology headways, and Gartner accepts that this pattern will continue in the years to come as technology continues to advance. However, for intrusion detection systems (IDS) to stay powerful in the always changing current environment, they should have the option to adjust and gain from past attacks. Accordingly, they should have the option to precisely recognize attacks that have previously surfaced, attacks that have quite recently been started, and attacks that are as yet hidden. Nonetheless, this investigation prompted the introduction of artificial intelligence (artificial intelligence) into intrusion detection systems. This element permitted the systems to advance on their own from recently gathered information and recognize new and startling attacks in view of the recognition of attack designs and other unidentified characteristics.

1.7 RESEARCH SCOPE

Machine learning takes into account various factors to work on model performance and accomplish occupations with exceptional adequacy. Here are a couple of occasions, which include: to resolve a particular issue, machine learning algorithms ordinarily use a deficient scope of element types. Since most machine learning algorithms are explicitly intended to

handle somewhat straightforward issues, this behavior can be made sense of by this knowledge. Nevertheless, considering that machine learning algorithms are intended to address a specific arrangement of challenges, this is for the most part the case. Conveying the mind boggling relationships that emerge between the essential information in the information stream requires numerous degrees of show. To recreate these perplexing interactions, deep learning is utilized; it does this by adding a few layers of representations to the information stream. Nonetheless, the necessity to model complex interactions among various information types aroused the attention of this machine learning subfield's headway.

A subset of machine learning called deep learning emphasizes the visualization of intricate relationships between informational indexes. This is additionally not quite the same as traditional machine learning techniques, which principally plan to address a definitive relationships that exist between informational indexes. In addition, a deep learning algorithm's layers have neurons with the ability to speak with neurons on isolated layers as well likewise with cells positioned close to each other. On the other hand, neural networks on various layers can establish communication thanks to deep learning systems. Neural networks contain deep learning algorithm coatings that speak with neurons arranged in other algorithmic layers. Consequently, these neural network-based layers of deep learning algorithms are in communication with neurons arranged in additional neural network-based layers. These levels are planned to be thought of as the "layers" while talking about the deep learning algorithm. "Deep learning algorithm layers" is otherwise called "layers of deep learning algorithms." Various techniques are utilized to construct different network architectures, and the specific mechanism utilized relies upon the kind of network being utilized. On the information that is input by the network layers, deep learning networks perform computations and transformations. Following the completion of these calculations and transformations, the outcome is shipped off the network layer beneath.

1.8 THESIS ORGANIZATION

Chapter 1 incorporates talks about the Internet of Things, machine learning, and intrusion detection systems. Additionally, this chapter gives a synopsis of the examinations that have been done on a few state-of-the-art approaches to intrusion detection systems in the context of the Internet of Things.

Chapter 2 gives a thorough explanation of the relative multitude of intricate components that make up the Botnet-Internet of Things benchmark dataset, such as a few stacking classifier architectures, cross-validation dataset parting, and categorical element encoding.

Chapter 4 incorporates the discoveries outline as well as the discussion chapter. rather than utilizing a solitary stacking classifier. It is feasible to create four particular stacking classifiers rather than only one by fluctuating the base and meta classifiers' application order. The suggested model's trying performance shows that incorporating it into intrusion detection system plans will deliver solid and satisfactory outcomes.

Chapter 5 incorporates a discussion of the investigation's outcomes, conclusions, contribution, and suggestions for the recommended system's future.

2. LITERATURE REVIEW

2.1 INTRODUCTION

The dissertation shielded in quest for the graduate degree concentrates on the cybersecurity of modern control systems from the standpoint of machine learning. The improvement of intelligent, trustworthy, and secure technologies for use in modern settings, with an emphasis on the assembling sector, is the primary objective of the Intelligent Secure Trustworthy Things (INSECTT) initiative [34]. The researchers have been exploring the utilization of machine learning techniques to meet the security needs of a compelling intrusion detection system. Machine learning is a highly effective method of separating pertinent characteristics from continuous network traffic. Additionally, by utilizing the learned models, machine learning can be utilized to help forecast both common and abnormal behaviors. The emphasis will be on surveying the adequacy and precision of machine learning (ML) detection methods as they are applied to intrusion detection systems (IDS) [35]. Breaking down the viability and precision of the detection methodology is a significant stage in each phase of an intrusion detection system's life cycle. The detection system's principal objective is to dependably and solidly distinguish an ongoing attack in an opportune and exact manner. In addition to being transformational, zero-day attacks are likewise ready to stay away from detection. Machine learning algorithms then make an effort to distinguish and order intrusions by delivering more precise predictions. This will straightforwardly prompt a diminishing in phony problems, which will further develop information examination.

2.2 INTERNET OF THING (IOT)

A huge assortment of sensors and contraptions are associated with the Internet through the Internet of Things (IoT), an organization that utilizes Internet Protocol (IP)- based correspondences. Clinical consideration administrations, early mediation, and distant reconnaissance can be made accessible to regulated or impaired people using the Internet of Things (IoT) in the wellbeing area [36]. Internet of Things (IoT) substances or people can integrate different parts, like sensors, actuators, radio frequency identification (RFID), and others. Think about, for instance. It is straightforward for guardians to utilize these labels and contraptions. One model given by Mawee Al-Mawee [37] is Internet of Things-

empowered applications that might peruse, distinguish, screen, and control data from RFID patients or patient labels (counting data about clinical hardware).

There have been various ways proposed in the past to ensure reliable correspondence between the hubs in an Internet of Things organization. It has, all the more precisely, proposed a powerful trust the executives framework expected for use locally based social Internet of Things setting. This framework would think about the numerous connections that exist between proprietors of socially connected contraptions. Three social connections are dissected to survey a hub's steadfastness: local area interest, genuineness, and participation. These three social connections are the objectives of assaults that incorporate self-advancement, knocking, and good mouthing, all of which plan to strengthen the organization's resilience [38].

It was found that keeping up with the trustworthiness of the hubs was essential to fostering a help model-based administration worldview for the layered Internet of Things. The sensor layer, the application layer, and the middle layer are the three layers that make up this design. An answer was in the end found by setting up a layered trust system, utilizing formal semantic language, and applying the fluffy set worldview theory. This procedure adds a third degree of intricacy to the circumstance, making it multiple times more perplexing than the proposed techniques. [39]

2.3 INTRUSION DETECTION SYSTEMS

Intrusion Detection Systems (IDS) are basic parts of safeguarding networks since they proactively look after network traffic, break down have communicated information to forestall security breaks, and set up fitting therapeutic activities. Subsequently, they act as the essential safeguard against online risks, speedily cautioning clients when endeavors at unapproved access are recognized. Intrusion Detection Systems (IDS) can be comprehensively isolated into two sorts: have based IDS, which are intended for a specific host gadget, and organization-based IDS, which track network traffic. No matter what the source, these plans are planned explicitly to sort and forestall unapproved access in different ways (interior or outside). In this way, the essential target of intrusion detection systems (IDS) is to safeguard organizations and PC systems by rapidly recognizing and forestalling destructive intrusions [40].

2.3.1 Host-based IDS

Intrusion Detection Systems (IDS) are basic parts of safeguarding networks since they proactively look after network traffic, break down have communicated information to forestall security breaks, and set up fitting therapeutic activities. Subsequently, they act as the essential safeguard against online risks, speedily cautioning clients when endeavors at unapproved access are recognized. Intrusion Detection Systems (IDS) can be comprehensively isolated into two sorts: have based IDS, which are intended for a specific host gadget, and organization based IDS, which track network traffic. No matter what the source, these plans are planned explicitly to sort and forestall unapproved access in different ways (interior or outside). In this way, the essential target of intrusion detection systems (IDS) is to safeguard organizations and PC systems by rapidly recognizing and forestalling destructive intrusions [40].

2.3.2 Network-based IDS

A network-based intrusion detection system's (NIDS) primary capability is to screen and assess network circulation to safeguard PC systems against threats originating from the network. Because of its capacity to assess traffic across several domains and recognize unauthorized access to a local area network (LAN), network intrusion detection systems (NIDS) are a vital and essential part of network security [42]. The detection methods of Natural Language Processing (NIDS) are used to screen approaching and active packets. These processes search for suspicious patterns and generate warnings that advise administrators of possible security risks. While using network intrusion detection systems (NIDS), a variety of network topologies may be used, including straight connections to switches, spanning port exploitation, and aligned connections. These abilities offer particular security measures tailored to the particular needs and specifications of industrial control systems, in addition to the standard security protocols used in the field of information innovation. A careful comparison must be drawn between various systems, along with a table illustrating each system's benefits and drawbacks, to facilitate comprehension. Intrusion detection systems (IDS) that operate at both the host and network stages are relevant in the domain of digital protection threat organization for the Internet of Things

(IoT). Each sort of IDS is discussed exhaustively in the sections committed to contextual request and a survey of the scientific literature [43].

Table 2.1: Intrusion Detection System Benefits and Drawbacks.

IDS Type	Advantages	Disadvantages
Host based IDS	- Comprehensive examination of the entire operating system and full communication stream. - Ability to detect insider attacks and scrutinize end-to-end encrypted communications. - No additional hardware installation required.	- Increased management efforts due to configuration setup required for each host. - Vulnerable to being disabled during certain denial-of-service attacks, potentially leading to functionality loss. - Resource consumption as OS audit logs occupy significant space. - Limited to monitoring local attacks on the installed machine, excluding broader network threats. - Possible delays in reporting attacks.
Network based IDS	- Detection of attacks through analysis of network traffic. - Surveillance of multiple hosts on the network for identifying suspicious activities. - Immunity to direct attacks and ability to evade detection by attackers.	- Difficulty in identifying attacks within high-speed encrypted traffic, particularly when network volume is overwhelming. - Inadequate data analysis capability in some networks due to limited monitoring port availability on switches. - Requirement of specific hardware for deployment. - Limited to identifying network-based attacks, excluding intrusions at the host level.

Architectures for network-based intrusion detection systems (NIDS) habitually incorporate various essential components. These elements are typically integrated to ensure viable network observing and defense against abnormalities. The first phase involves assigning labels to data-gathering devices and distributing them around the network architecture to screen particular processes or activities. As a result, these devices mostly classify the data, giving crucial insights into how the network functions. However, an additional crucial part — an indicator motor — allows the obtained data to be compared with previously resolved rule sets. At the point when it detects deviations from the network's usual activities, the Network Intrusion Detection System (NIDS) will alert the user [44]. This serves as a warning to users about possible risks or disruptions. Consequently, a crucial part of the NIDS design is the storage module, which is in charge of monitoring the standard sets that the detection motor uses all through the data dispensation stage. This module is responsible for ensuring that assessments are carried out really and that irregularity empathy is accurate. Additionally, the NIDS reaction component performs prepared tasks in response to an active alarm. Then again, the responses could be as aggressive as strongly impeding malicious packets or as more passive as illustrating the activity for human survey and judgment. All of these responses are equally possible. The incorporation of machine learning (ML) techniques into

the design of new intrusion detection systems (NIDS) has the potential to enhance their anomaly detection capabilities. When these processes are finished, elegant algorithms will be retained to recognize and respond to emanant threats with enhanced accuracy and efficacy.

The following is an illustration of a typical IDS construction:

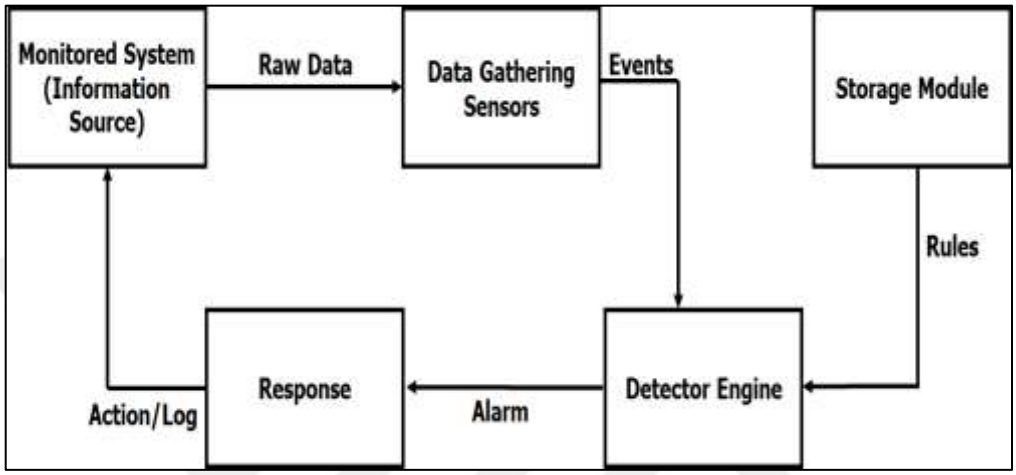

Figure 2.1: Displaying The Architecture of The Intrusion Detection System.

While they wait for convenient responses, creators are looking out for real-time network observing solutions. Three behaviors are indicative of intrusions or assaults that are distinguished by both NIDS and HIDS:

a. Detection based on signatures [45]

b. The detection of behavior [46]

c. Hybrid detection, also known as specification-based detection

2.3.3 Signature-based Detection

A large database containing pre-existing vulnerabilities is the foundation for abuse detection, sometimes referred to as signature-based detection. The system finds attacks by first analyzing network traffic to look for specific patterns, or signatures, and then cross-referencing those signatures with database information. Not only does this method require little work, but it also yields excellent results in terms of identifying recorded attacks. Cisco Systems, for instance, uses enormous attack databases to protect industrial settings, with a particular emphasis on the DNP3 and Modbus communication protocols. Tools like SNORT

and BRO, which are available for purchase or use under open-source license, can improve detection performance [47]. But now, these technologies are unable to detect zero-day assaults with any degree of accuracy. For intrusion detection systems that rely on signature information to function as efficiently as possible, manufacturers must maintain their rule sets and signature databases on a regular basis. Throughout the year, these changes are regularly and regularly applied. Signature-based detection is still a widely used technique in many different industries, including water treatment and electrical power systems, even though it is not the best option for safeguarding Industrial Control Systems (ICS). It is standard practice to integrate with other, more complex security models in the goal of providing complete security.

2.3.4 Behaviour-based Detection

According to Kaouk et al's. research, behavior-based detection can forecast the normal behaviors of the system and network. Not at all like signature-based detection, this technique not just avoids the requirement for pre-established norms yet additionally notifies managers when their behavior does not fit pre-established standards [48]. The system's capacity to identify zero-day assaults is an imperative advantage, facilitated by the lack of pre-established rules. Furthermore, it adds another barrier to the already troublesome task of hostile actors attempting to ascertain the intrusion detection system's capabilities. Then again, behavior-based detection systems habitually have inconvenience accurately distinguishing the kind of attack and generate a sizable percentage of false positives. Indeed, even with researchers' best efforts to consolidate several approaches to address these shortcomings, the detection rate of stand-alone behavior-based systems is still excessively low. In addition, the architecture of the framework used in behavior-based detection could present new challenges on top of the ones right now present.

2.3.5 Specification-based Detection

Specification-based detection, according to Hajiheidari et al., is a half breed strategy that can be created by consolidating behavior-based and signature-based detection techniques. Machine learning techniques are used to strengthen this mixture strategy. It is projected that in the forthcoming years, the crossover detection method will witness a surge in popularity inside the developing industrial control systems (ICS) market[49]. Half breed detection

offers a more significant level of total detection precision by joining these two approaches. By getting rid of detection gaps welcomed on by false positives and false negatives, this is accomplished. The survey results indicate that the successful application of machine learning algorithms has the potential to significantly improve cyberattack detection. As such, this strategy is considered a workable plan for strengthening cybersecurity defenses. The accompanying figure shows how intrusion detection systems are categorized based on how they are installed and distinguished.

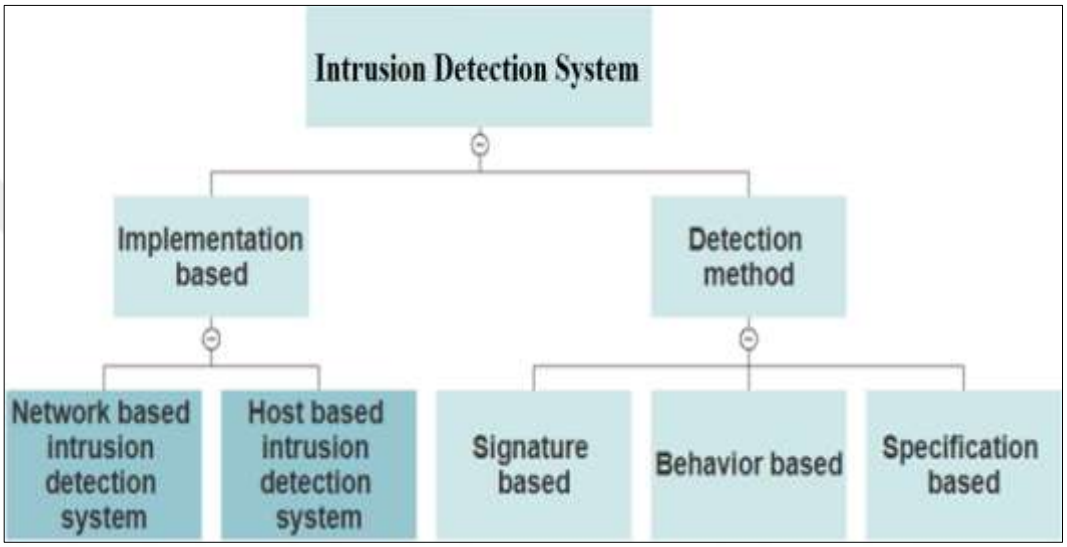

Figure 2.2: Techniques for Classifying Intrusion Detection.

2.4 TYPES OF IOT ATTACKS

IoT networks have been the subject of numerous security issues; nevertheless, the most successive IoT assaults are as follows:

2.4.1 Physical Attacks

A physical attack is the process by which an outsider attempts to physically access an Internet of Things (IoT) gadget. The best places for Internet of Things devices would be safe places. Nonetheless, this may not always be possible because the majority of cybersecurity threats come from inside an organization [50]. Because of the development in the frequency of physical breaches set off by malicious code conveyed via USB sticks, it is critical to foster artificial knowledge-based security solutions to secure electronic devices and the data they

store. The aforementioned solutions must be tried to shield Internet of Things devices from physical attacks and to diminish the risks related to gadget operation and data uprightness.

2.4.2 Encryption Attacks

Decoded Internet of Things (IoT) gadget transmissions are vulnerable to capture by unauthorized individuals, who may then save the material for later use, according to a study published in 2021 by Mohindru and Garg. The research indicates that assuming the encryption key is compromised, attackers may have the option to take over the server without authorization and use their own methods. That being said, it is not implausible that this may happen. Encryption contributes significantly to the overall network safety of the Internet of Things (IoT) by safeguarding data uprightness and privacy. Additionally, it aids in the defense of the risks associated with unauthorized access, IoT system operation, and the data they contain [51].

2.4.3 DoS (Denial of Service)

Attacks known as denial-of-service (DoS) aim to temporarily stop websites and other facilities from operating. Munshi et al. (2020) claim that botnets can construct countless devices to satisfy many service needs simultaneously, which enables them to launch coordinated attacks against a single target. These attacks may not have data theft as their primary goal, yet they can nonetheless cause significant harm to organizations. Businesses must design strong defenses against denial-of-service attacks to safeguard progressing operations and business congruity. Also, DoS attacks have the potential to cause financial losses, reputational damage, and customer resentment even in the absence of data theft. Thus, safeguarding against such attacks is crucial to maintaining the consistency and adaptability of corporate operations.

2.4.4 Firmware Hijacking

A study by English [52] tracked down that failing to update the firmware on Internet of Things (IoT) devices raises the possibility that cybercriminals will take advantage of it. It is crucial to affirm the authenticity of update sources to stop bad actors from gaining admittance to your gadget and installing malware. Authenticating the update source can be

troublesome because most hardware types don't have cryptographic signatures from vendors. This emphasizes the significance of being cautious and setting up strong security measures to lessen the risk of unauthorized firmware updates and possible exploitation by digital adversaries.

2.4.5 Botnets

The possibility for Internet of Things (IoT) devices to be maliciously repurposed into somewhat controlled bots was demonstrated by Shi [53], who described the Mirai botnet attack. Botnets use these keen, networked devices for a variety of malevolent purposes, including as disabling gear and disseminating confidential company information illegally, which is habitually sold on the dark web. Furthermore, there is a serious risk to enterprises since botnets could use these hijacked devices to obtain and sell sensitive company data. Since Mirai has infiltrated millions of IoT devices, the threat it poses is still significant, underscoring the continuous difficulties with IoT security and the necessity of strong defenses to counter such threats.

2.5 MACHINE LEARNING ALGORITHMS

By distinguishing the various types of packets in the traffic and performing other essential computations and choices, machine learning algorithms can enhance network security. The accompanying categories apply to machine learning algorithms:

2.5.1 Supervised Algorithms

For supervised machine learning algorithms to appropriately recognize network intrusions, Ahmed [54] emphasizes the requirement for adequately labeled class data. The dataset is partitioned into subgroups for testing and training during this methodology. Training algorithms to fabricate a model that can use labeled data to foresee unknown instances in test data is the main goal. Data inputs from hosts or networks are classified as either normal or as intrusions (attacks). Classification or regression techniques are used to look at the relationship among labels and info data. During training, algorithms track down important categories and attributes. Eliminating unnecessary features is aided by feature selection. During the testing stage, algorithms make predictions about anomalies and the class they

have a place with based on as of late gathered data. Supervised machine learning models are much of the time altered to suit particular use cases, including trade procedures or protocols. Various methods are oftentimes used for intrusion detection, including Naïve Bayes, K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and Artificial Neural Networks (ANN). Supervised learning performs well in recognizing known assaults, however may struggle to identify unknown threats.

2.5.2 Unsupervised Algorithms

Unsupervised learning, according to [55], builds models from unlabeled data by using clustering techniques. These algorithms are able to differentiate hostile inputs from host logs or network traffic by evaluating the statistical characteristics of the data with no earlier information. One important advantage of using unsupervised techniques, as featured by Nisioti et al., is that they don't need laborious data training processes. They are adept at choosing features, and they take the data structure into account while partitioning input data into clusters that advance relevance and diminish redundancy. A threshold is set during analysis, with an emphasis on the quantity of typical occurrences as opposed to anomalies. Each is given a novel score once clusters based on relationships have been created. A cluster is considered malevolent in the event that its score is higher than the cutoff. According to Yu et al., this means that whereas attacks are typically discovered in smaller clusters, ordinary traffic tends to cluster into larger clusters. This technique turns out to be more successful than the training phase of supervised learning. Without labeled data, unsupervised learning can also distinguish unknown risks like zero-day assaults, albeit with a high false-positive rate. According to Zaman et al., K-means clustering, fluffy clustering, and hierarchical clustering are often used methods in unsupervised learning.

2.5.3 Hybrid algorithms

Crossover machine learning techniques have been created in response to the developing cybersecurity climate to address various issues related to intrusion detection systems (IDS). The goal of these cross breed algorithms is to work on the overall performance of the system by bringing down the quantity of false-positive and false-negative alarms, based on the research of Nisa [56]. Half breed approaches are those that consolidate supervised and

unsupervised machine learning techniques. By using the best aspects of each approach, half breed approaches aim to maximize intrusion detection accuracy.

Generally speaking, crossover models join the accuracy of supervised algorithms for known attacks with the detection force of unsupervised techniques for unknown threats. As a result, crossover models can work better. Information innovation based conventional solutions couldn't be adequate given the possibility that cyberattacks are always changing, including the techniques they use. The efficacy of intrusion detection in networks can be enhanced by half and half classifiers by breaking their duties into discrete parts that handle pre-processing, classification, and clustering.

Scholars from many academic establishments have examined crossover algorithms as a possible approach to augment intrusion detection. The crossover strategy created by Anton et al., which combines the Bayes algorithm and the Support Vector Machine (SVM) technique, is an illustration of this. While the decision tree and Naive Bayes methods both recognize known anomalies and unknown anomalies, respectively, the support vector machine (SVM) philosophy separates data into normal and abnormal occurrences. By beating the limits of separate algorithms and obtaining an accuracy of 80.68 percent and a detection rate of 1.57 percent, this technique showed promise for enhancing the intrusion detection system's (IDS) overall performance [57].

Furthermore, a range of crossover strategy applications used in intrusion detection are covered by Pranggono [58]. They give a technique to network intrusion detection that was advanced by Fovino et al. to assist with distinguishing sophisticated attacks that target SCADA systems. This model combines methods that are supervised and unsupervised. The application of these crossover strategies shows how integrating the supplementing benefits of several distinct machine learning algorithms may be used to tackle present day cybersecurity threats successfully.

2.6 MACHINE LEARNING CLASSIFIERS

Section 2.6's subsequent subsections offer a survey of the literature on various intrusion detection systems that make use of traditional machine learning classification models. Lazy-

based and instance-based learning classification models, as well as non-linear models for binary and multiclass classification, are shrouded in this section.

2.6.1 K-Nearest Neighbours

K-NN, also alluded to as K-Nearest Neighbors, is a supervised learning strategy used for regression and classification problems. Its fundamental capability, which is to choose just the nearest data points from the specified data point, is reflected in its name. The neighborhood of K-point is prohibited for the threshold, which served as the foundation for the choices. As a result, in the event that K = 1, the main Newtonian data points used to make decisions are those in the test data points' immediate neighborhood [59]. In such a mind boggling data space, the Manhattan, Cosine, Euclidean, or Manhattan similarity measure is what essentially distinguishes the K-nearest neighbor analysis. The operations being performed here are those on the distance between data items, where each component belongs to a sort that is either identical to itself or to other elements of the same kind. Accordingly, a distance of zero denotes identical elements, while a distance greater than or equal to zero denotes dissimilarities.

This specific K-NN strategy characteristic acts as a differentiator between K-NN and convolutional neural networks, which use a greater number of training and feature extraction cycles. As a result, K-NN showed us how to classify proficiently without having to wait for the training step. Because it contributes to an ideal scenario, this characteristic makes the K-NN classifier the obvious decision for classification tasks.

$$distance(T1, T2) = \sqrt{\sum_{i=1}^{n}(q_{1i} - q_{2i})^2} \tag{2.1}$$

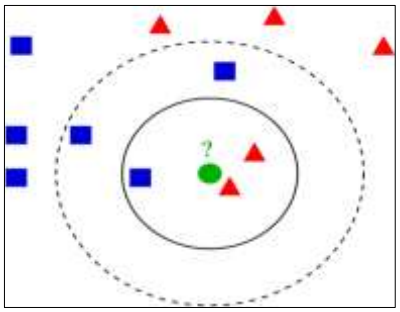

Figure 2.3: Three Neighbours and the K-Nearest Neighbour Classifier.

2.6.2 Random Forest

The random forest method is extensively utilized in many various domains, such as value estimate and pattern acknowledgment. Ullah et al. (2018) emphasize that decision trees with numerous samples, majority deciding in favor of classification, and regression averaging are the methods used to achieve this. Because the Random Forest procedure can relate both quantitative and categorical data, it tends to be used for both regression and classification issues. One of the most crucial aspects of this system is its lack of coercion.Random forest is used in classification problems because it generally produces higher classification performance than other strategies. In addition, it employs a strategy known as "bagging," also known as "bootstrap aggregation." In this case, a random subset of the dataset is chosen, and the quantity of bags is the same as the rows in the table. It is possible to generate replacements and sample randomly in parallel. In this way, each and every model was trained freely on each bootstrap sample. A diverse representation in the models will result from accurate column sampling [34].Because of this, each model produces an alternate set of future scenarios. All of the models vote to decide the final result, and the plot is shaped by the impact of each contending model. In the meantime, the models offer their predictions, and the vote's result determines the majority's final decision. This approach will always be applied as the accuracy and consistency of the results generated by the random forest algorithm develop.

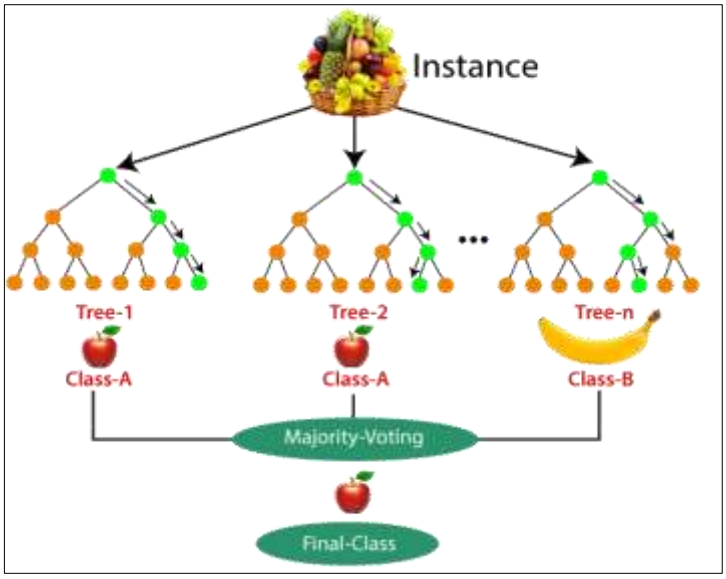

Figure 2.4: The Majority Voting System Used in Random Forest to Make Final Decisions.

2.6.3 Support Vector Machine

The majority of linear classification issue solutions use support vector machines (SVM), a statistical device, and an author [43] argues in favor of SVM's high accuracy level. Assigning classes to inputs is the occupation of binary classifiers, which is what support vector machines do. In general, SVM is able to separate the inputs into two classes — for example, feelings that are favorable or negative. A hyper plane, or straight line, is positioned in the two-dimensional field of view to split the classes; the classification line is drawn at a point that permits the greatest possible separation between the classes.

The challenge is in selecting a support vector that is both reasonable and actually identifies the hyperplane's domineering jerk. There is a great deal of variation between the selected support vectors; the optimal hyperplane is the one that can best gap groups apart. As a result, the vector that represents the hyperplane over this ideal is retained by the plane that separates the data for positive and negative emotions. Two data sets are isolated by the plane, which acts as a decision boundary.

Non-linearly classifiable data, then again, is handled by SVM, which uses kernel functions like polynomial, Gaussian, and RBF. This applies to linearly separable data. By using hyper planes, these processes simplify the classification process by smoothing out the low-dimensional feature into a more significant level as well as the other way around.

At the point when various classes are present, the integrated classification strategy outperforms SVM techniques in terms of effectiveness. This strategy uses several SVMs to address the classification issue in a careful manner. Lib-SVM, sequential least optimization, and blunder remedy yield code are a couple of notable multi-class support vector machines (SVM) frameworks that work on the adaptability and usefulness of SVM in a variety of classification applications, allowing for proficient classification across several classes.

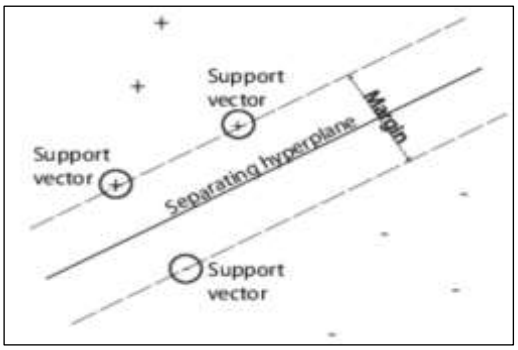

Figure 2.5: A Support Vector Machine Classifier For Problems Involving Binary Classification.

2.6.4 Multi-Layer Perception

According to Khater [51], neural networks are particularly successful classifiers in the field of machine learning because they can replicate the functions of the human nervous system. Neural networks imitate the millions of neurons in the human brain that are each in charge of decision-making and information transmission. These connections are created through a process called "detritus," which improves communication and information sharing effectiveness.

Three basic types of layers make up artificial neural networks: input, stowed away, and yield layers. The information layer gathers sentiment data attributes and applies the appropriate labels. The feature values in the internal layer are duplicated by the respective weights prior to being added together to indicate bias values. In contrast to feedforward networks, which have a one-way data stream, backpropagation networks transmit information to the two antecedents and posteriors.

The most important strategy for updating a system is gradient descent, which is used to estimate the weights of various system components in the best possible way. The strategy for selection involves iteratively applying and tweaking weights until the weights produce the best results. Neural network effectiveness is therefore crucial in addition to several other factors like the quantity of nodes in each secret layer, the learning rate, the quantity of epochs (training repetitions), and the architecture of stowed away layers. For the best categorization, these factors must be precisely adjusted.

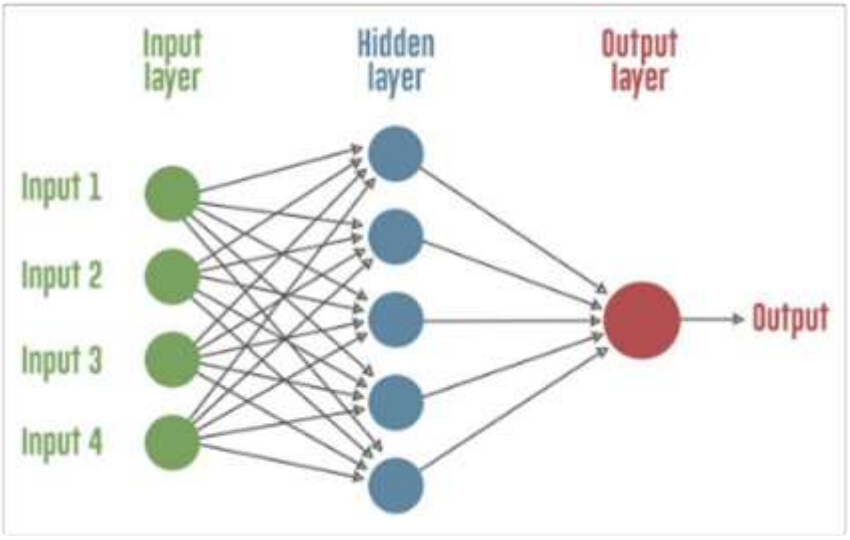

Figure 2.6: The Quantra E-learning Portal's Artificial Neural Network Architecture.

2.7 MACHINE LEARNING BASED INTRUSION DETECTION SYSTEMS

The previous year, they led a comparison between profound learning and machine learning models, and their findings supported the thought that machine learning-based secure artificial intelligence systems are capable of distinguishing malicious material. The study aims to decide whether public trusts AI-based technologies and whether these firms can be trusted to handle sensitive data. The main takeaway is that these machines are unimaginably precise, however they can also work in teams to accomplish troublesome jobs that require human labour. Four unique approaches are remembered for profound learning: GRU, LSTM (one and two), and LSTM (one and two). Decide the necessary tools: Included are the Wireless Sensor Detection System (WSN-DS) and the KDDCUP 99 dataset. The Wireless Sensor Network Detection System (4.2) and the KDD Cup's network intrusion dataset require the advancement of detection mechanisms that are linear in relation to the sort of assault. In this work, the performance of eight distinct categorization algorithms was skill fully evaluated by consolidating groups of qualities with whole sets. It was resolved whether the executed measures were compelling by using metrics like accuracy, precision, recall, and F1-scores. Building trust in the realm of intrusion detection is crucial with regards to information security. Thus, the idea of working on the interpretability of AI techniques by using data, procedure, and master accountability is put out in the accompanying statement.

The research work by Popli et al. (2021) incorporated current technologies that allow for adaptability to the dynamic nature of MANETs to foster appropriate security methods for them. To do this, an enhanced security solution can be found by studying the ongoing MANET technologies or solutions. The related technologies that will be shrouded in this article are machine learning, artificial intelligence (AI), hereditary algorithm-based approaches, bio-inspired algorithms, and others that are always creating and changing. The venture's primary goal is to completely and precisely investigate the several security enhancement techniques presently being used in MANETs. The goal of this endeavor is to make it a reality.

In this paper (Jadhav and Pellakuri, 2021), the issues arising from unprotected and circuitous machine network connections are addressed by the application of two methodologies: machine learning techniques and HDFS data storage. As part of the extensive study process, intrusion detection system (IDS) checking is involved. The design strategy for TP-IDS (Time-Phase Free Self-Healing Dynamical Systems) is based on a two-step process in which some deviations are left to be addressed at each stage and then addressed at the accompanying one. k Nearest Neighbors (kNN) and Support Vector Machines (SVM) are utilized in the first step of the TP-IDS algorithm construction process. The Decision Tree (DT) and Parsimonious Bayes (NB) components are converged in the validation phase because they have the potential to further develop accuracy. Furthermore, Hadoop will serve as the cornerstone foundation for infrastructures related to data processing and storage for the foreseeable future. As a result, parallel processing can be integrated to boost system performance, leading to TP-IDS's increased productivity.

The primary finding (Ponnusamy et al., 2021) highlights that it is so challenging to create machine learning models that can withstand attacks specific to the Internet of Things because of the lack of network traces and logs. The wireless intrusion detection is designed to present the main design challenges that a wireless intrusion detection system would have when used for the dataset qualities that are currently accessible, as compared to the KDD cup dataset. Various futuristic approaches, including yet not restricted to sophisticated techniques discovered in the literature, have been suggested for traffic gathering in wireless networks (WNs). This paper's first patch examines various approaches to data unloading, acquisition, and breach detection. The peculiar design problems that surface while sending intrusion

detection systems in wireless segments were noted throughout the span of this venture. Because of the inborn intricacy of the system architecture, the sending process of an intrusion detection system requires more care while operating on wireless networks as opposed to wired ones. The article that follows describes a conventional approach to installing an intrusion detection system that is wire-based and explores potential ways to expand these techniques to a wireless setting. The arrangement methodologies for wireless intrusion detection systems are the primary subject of this article, which also discusses potential future trends and uses for these technologies in wireless domains. The secure operation of often taken advantage of technologies, such as wireless sensor networks (WSNs), self-organizing mobile networks (MANETs), and the Internet of Things (IoT), has turned into a serious challenge that requires several studies.Gaining a more profound understanding of how wireless environments will foster in what's in store requires doing this. An intrusion detection system that can productively examine network traffic, especially across wireless networks, is therefore required.

As opposed to Akram et al's. 2021, this article offers a useful procedure created for distinguishing an attack in medical electronic systems that uses an adaptive neuro-fluffy derivation system. An adaptive neuro-fluffy surmising system at the focal point of this strategy is able to change predictions in real time dynamically. Making sure treatment network security is safeguarded is one of the main goals to forestall cyberattacks on PHR network storage. This strategy has revealed a snippet of information: malicious network traffic can be perceived and analyzed by the defense mechanism by design. By putting a suggested security model to use on an actual network, tests are used to affirm its security. The accuracy of previous research is based on test and training yield data as well as the application of the ANFIS model in real time on the MATLAB platform.

The findings of this study (Dat-Thinh et al., 2022) indicate that the Intrusion Detection System (IDS) MidSiot has the capacity to be installed on both Internet and local Internet of Things (IoT) gateways. The proposed Internet of Things (IDS) would consist of the three stages listed underneath: recognizing the various types of IoT devices that are present in an IoT network, distinguishing among malicious and harmless network data, and perceiving the various kinds of attacks that can be launched against IoT devices. A local gateway is responsible for managing the first stage, which entails using the computational resources

given by peripheral devices. The Internet gateway is in charge of overseeing the final two stages. The evaluation findings show that the proposal can distinguish seven normal intrusions against IoT devices with an average detection accuracy of 99.68 percent. This is an improvement in detection accuracy over the most advanced IDS available today. IoTID20, CIC-IDS-2017, and BOT-IoT are three notable intrusion detection system (IDS) datasets that were used in the assessment. The proof gave leads one to the conclusion that MidSiot is a useful and compelling intrusion detection system that is appropriate for securing Internet of Things networks.

The authors of this paper (Liu et al., 2022) propose an approach to intrusion detection based on machine learning algorithms and evolutionary computation that combines the k-Nearest Neighbor (kNN) algorithm from machine learning with the Arithmetic Optimization algorithm from evolutionary computation. The goal of this approach is to fabricate an edge intelligence framework that can recognize and eliminate an outsider attempting to compromise the WSN by using a network that repeats request messages. The authors proceed to say that carrying out the scorched earth approach could improve intercultural communication. Rather, during this model's optimization, Lévy flight strategy mode is used to work on the precision of the model. The kNN classifier's accuracy in benchmarking functions is significantly higher than that of contending methods, making it a strong candidate for improvement. Conversely, each author will use Matlab2018b to execute the simulation in parallel. The kNN-based model can recognize CISUS with a close to 100% accuracy rate, which is around 10% better than the kNN-based model working alone. This guarantees, among other things, the quality control of research, and the subsequent academic dissemination stage involves publishing the findings in scholarly publications for peer audit. Furthermore, based on the findings, it is obvious that it is successful and generalizable to other settings.

In their study from 2022, a team drove by Akshay Kumaar develops a scenario named "ImmuneNet," a half breed system that uses profound learning techniques to distinguish and forestall aging processes early on. The purpose of this carpet's pilgrim is to safeguard medical data. The strategies used to accomplish the desired goals of enough accuracy, effectiveness, and a consistently preserved crude structure are feature designing, class balancing oversampling strategy, and hyperparametric optimization. This architecture's

design is extremely powerful, space-effective, and compatible with the Internet of Things, which makes it a strong candidate for the creation of intrusion detection systems on medical hardware and healthcare systems.

It is composed of less than 1,000,000 traits. The Ringer DNS 2021 datasets from the Canadian Digital protection Institute and the 2017-2018 Intrusion Detection System datasets are used to evaluate ImmuneNet's effectiveness in comparison to other machine learning techniques. These datasets are a goldmine of cutting-edge, real-time data relevant to cyberattacks. Tested on the CIC Chime DNS 2021 dataset, ImmuneNet performs better compared to all other approaches, with an approximate 99.19 percent accuracy, 99.19 percent recall, and 99.2 percent ROC-AUC score. The results of this investigation are on par with the best practices currently being used for distinguishing between valid requests, intrusions, and other types of attacks; in fact, they slightly outperform those practices.

To safeguard the network of linked medical devices being scrutinized, the authors of the research paper (Thamilarasu et al., 2020) have considered and constructed an original mobile agent-based intrusion detection system. They also undertake an analysis and presentation of their findings. The self-contained, hierarchical structure that has been suggested is viable. This is accomplished by utilizing machine learning and regression techniques to track down anomalies in the gathered sensor data as well as network intrusions. Top to bottom studies and hospital network geography simulations are carried on a mission to work on understanding of the workings of many subsets that make up the medical Internet of Things. These subgroups incorporate wireless body area networks and other networked medical devices. Based on the simulation results, it is possible to achieve a serious level of detection accuracy with a small amount of resources, which is a promising conclusion.

2.8 COMPARATIVE STUDY OF EXISTING MACHINE LEARNING BASED IDS

Quantity analyses of several IoT data-based intrusion detection systems are shown in the table underneath. It includes details about the dataset, the models used for classification, the optimization models used to choose features, and performance analysis based on accuracy metrics. The performance of various intrusion detection system models, which are regarded as state-of-the-art, is analyzed in the table that follows. The table contains the title of the

research, the dataset that was used, information about the prescient model, and an intensive survey of the model's performance.

2.9 SUMMARY

The efficacy of earlier intrusion detection models in forestalling attack classes such as denial-of-service (DoS), testing, R2L, and U2R was also shrouded in this chapter. The models that were previously stated were multi-facet (ML), profound layer (DL), and ensemble (DL) models. Furthermore, these particular goals were achieved, and a conversation about potential advancements in intrusion detection model innovation in what was in store took place. Over the span of the occasion, participants discussed various model vulnerabilities and emphasized that setting up an intrusion detection system that complies with industry standards is so important. Numerous significant discoveries were carefully examined, and it is anticipated that this information would be useful in the creation and working of the expected standard model.

3. RESEARCH METHODOLOGY

3.1 INTRODUCTION

This chapter offers a comprehensive survey of many planned experiments designed to evaluate the effectiveness of intrusion detection techniques using benchmark datasets inside the Internet of Things (IoT) framework. The purpose of proceeding to present these tests was to evaluate these policies' usefulness. A comprehensive synopsis and explanation of the datasets and instruments used in these investigations are given. Several iterations of the process are typical, with each investigation focusing on an alternate aspect of the answer. Accuracy is the primary measurement used in this strategy to estimate performance. The goal is to ascertain the exact capability that each part of the solution provides to the overall classification. The chapter also gives a description of various experiments that were supposed to evaluate interference detection systems' effectiveness by using an ensemble accumulating classification model. Gaining understanding of how each component of the solution contributes to the ultimate classification result is the goal. The assessments are carried out using a benchmark dataset that is available to people in general and was created for the Internet of Things BotNet. The dataset covers a wide variety of intrusion attack types.

3.2 PROPOSED RESEARCH FRAMEWORK

This chapter provides a careful outline of the suggested research approaches in the fields of cybersecurity and machine learning-based intrusion detection systems for the Internet of Things. The first step in identifying Internet of Things invasions is selecting a baseline dataset. A variety of discrete incursion classification types are remembered for this dataset. These incorporate TCP, UDP, Sync, Combination, and Clean up, to name a few.The purpose of this research-generated dataset is to share it with other subject matter specialists so that additional scientific investigation can be aided.

The four main phases of the suggested system are as follows:

The information gathered through the Internet of Things (IoT) is encoded to make it suitable for use as the basis for a feature vector.

Using the holdout cross-validation resampling method, the dataset is separated into segments with a 70/30 percentage distribution. 70% of the features and their accompanying labels make up the training set. The testing set receives the remaining about a third of the features, which is used for model validation.

As the ensemble classifier was being created: Four distinct classifiers are integrated to create a stacking-based ensemble classifier. In addition, the system uses a fourth classifier, whose conclusions are found from the results of the first three classifiers, and three base classifiers.

Validation and Performance Assessment: The testing set's goal is to check a wide variety of stacking classifiers, each with an alternate configuration. The performance evaluation procedure uses machine learning estimation parameters trying to give a more precise categorization model. To achieve the best system proficiency, classification model performance and classification parameter optimization are made possible by the application of the cross-validation approach.

Using the cross-validation approach, the dataset is separated into two discrete sets: the train set and the test set. The stochastic cases from the two sets assist with achieving this. The main goal is to use extensive testing and model refining to maximize the efficacy of intrusion detection systems for the Internet of Things (IoT).

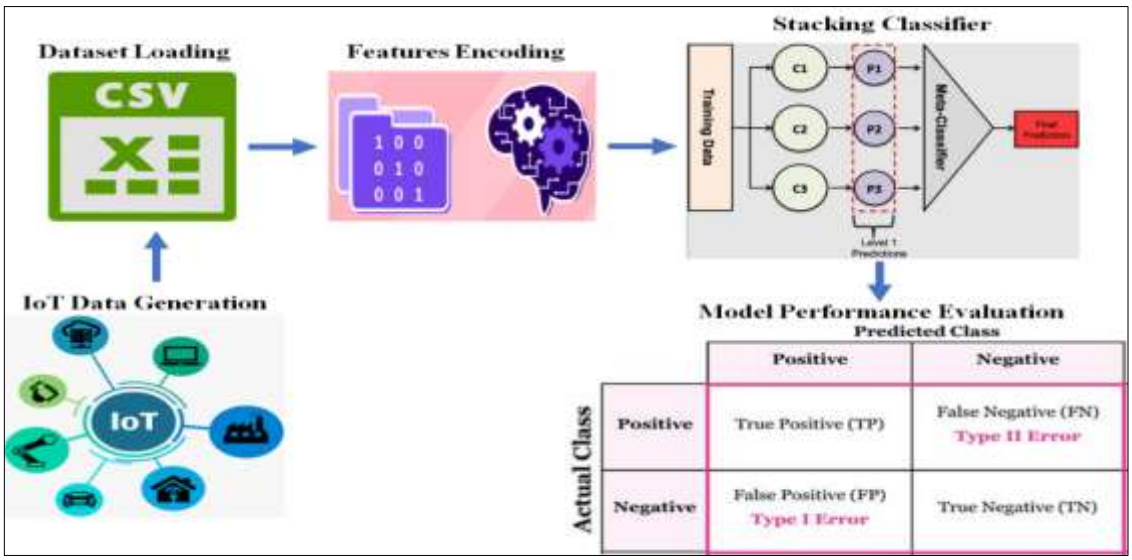

Figure 3.1: Proposed Intrusion Detection System.

3.2.1 Dataset

Citations from Shi and Sun (2020) and Koroniotis et al. (2019) suggest that the dataset used is one of the most ongoing available in the area. The assortment is made up of extensively changed Wireshark traffic that was captured when nine Internet of Things (IoT) devices were associated with a centrally switched local network. Its features incorporate 23 statistically designed attributes that were taken from the.pcap files. A couple of more were also created using statistical methods.

The seven statistical measures in this dataset are distinct because they were delivered using a decay factor of 0.1 inside a ten-second time period. The process used to do this is remarkable. Metrics including the mean, variance, count, radius, magnitude, covariance, and correlation coefficient are remembered for this category. The decay factor value L 0.1, which indicates the time span inside the dataset that corresponds to the decay factor value, is present in both the articles and the dataset.

The information in the pcap record relates to four basic characteristics: the quantity of packets that are sent, the degree of jitter, the size of just friendly packets, the size of both approaching and active packets, and the length of transmission for each cordial packet. It's interesting to take note of that the most important part in extraction turns out to be the total number of packets conveyed. It is possible to calculate a total set of 23 attributes because

each of these qualities has statistical measures that are obtained by applying at least three statistical measures.

The suggested model can perceive automatically nine various types of attacks: TCP, Combo, Junk, Scan, Ack, and Syn. Table 3.1 provides a detailed analysis of some of the BoT-IoT dataset's part parts.

Table 3.1: Bot-IoT Dataset Attributes Description.

Attribute	Description
Pkts_sent	Number of packets sent out from the source to the destination
Pkts_received	Number of packets received by the destination from the source
Latency	Time taken for a packet to travel from source to destination
Protocol	Network protocol used for communication (e.g., TCP, UDP, ICMP)
Port	Port number associated with the communication
Payload_size	Size of the payload transmitted in each packet
Source_IP	IP address of the source device
Destination_IP	IP address of the destination device
TTL	Time-to-live value indicating the maximum number of hops for a packet
Flag	Packet flag indicating its status or purpose

3.2.2 Feature Encoding

In the discipline of data science, preparing the data is a crucial step that needs to be finished prior to starting the demonstrating process. It is accepted that one of the most important components of the activity requirements is the encoding of categorical data. Although machine learning models are primarily designed to work with number values, they can also handle other forms. Category string values make up the great majority of data that is seen in

real-world scenarios. Categorical data must be translated to number format to make the mathematical operations necessary for demonstrating easier. This is carried out to satisfy the demonstrating requirements.

By using categorical data encoding, which expedites the process for models to obtain data with changing category values, enhanced expectation capabilities can be achieved. This academic paper examines the significance of encoding categorical data all through. The Single-Hot The encoding strategy is a usually used procedure wherein a variable specified for each category in the dataset is assigned an extraordinary binary value, either 0 or 1. It is that value that represents that category. Usually, this encoding strategy produces binary features, which are alluded to as artificial variables. This is explained by the fact that these qualities have no intrinsic statistical significance. With regards to representing data that has no real relevance, this kind of encoding is really useful. The quantity of sham variables required is straightforwardly correlated with the total number of categories in the dataset. These variables are alluded to as "sham variables" because they have no intrinsic meaning and are solely used for encoding.

Point of fact, one-hot encoding is a strategy that is regularly used to prepare data. Binary variables with the value N-1 are regularly used; N is the total number of categories; this ensures that each category is encoded. The approach that follows can be used to encode any categories that are not specified in the N-1 columns. It is normal practice to use N-1 binary variables in regression analysis. All that is expected to accomplish this is to eliminate the first or last segment from the as of late created One-Hot Encoding.

Using all N columns is the most proficient way to handle categorization problems. Then again, with regards to tree-based techniques, building trees with the most ideal amount of variables — as much as it is practically possible — is preferable to using a majority-based strategy. Additionally, this ensures that each feature is completely examined in the training phase, which is necessary for linear regression to achieve the desired number of degrees of opportunity. Because binary variables by definition contain all relevant information about the original categories, linear regression can make full use of the N-1 binary variables to acquire all relevant information about the variables that were initially associated with the categories.

To train various machine learning techniques, such as neural networks, support vector machines, and clustering algorithms, all of the features must be analyzed simultaneously. All of these methods can be used with this process. Using N-1 binary variables — which enable quick training and expectation — these algorithms are able to gain an intensive understanding of the original categorical variables.

3.2.3 Stacking Classifier

By aggregating the outputs of many Regressors via meta-classifiers or meta-Regressors, stacking increases the forecast accuracy. This technique uses the full training dataset to train meta-models by using the Regressor's outputs as features.

Furthermore, heterogeneous stacking offers a variety of learning strategies at the starting level, which accounts for its frequency. It is anticipated that classifiers, K-nearest neighbors, random forest, and simple Bayesian classifiers will be used while utilizing a condensed stacking strategy. The predictions of those are joined via logistic regression to allow for the creation of an integrated met classifier. Learning curves give proof that stacked classifiers produce countless result limits, which allows them to beat single classifiers in accuracy positions while avoiding overfitting signals.

Stacking is a typical strategy used in data science platforms like Kaggle that has been shown through empirical proof to be powerful. The triumphant passage in the Otto Gathering's item classification contest, which used layering with in excess of thirty distinct models, serves as an example of this. The effectiveness of the three meta-classifiers — XGBoost, Neural Network, and Adaboost — was improved by using the result from these models as features.

One crucial use of this procedure is stacking, which involves changing over the predictions made by main classifiers into new features that are then used to train meta-classifiers. Each classifier can be considered a meta-classifier. Figure 1 shows the training process for three unique data-sorting classifiers. To achieve accurate overall predictions, individual forecasts should be summed up and then sent into the meta-classifier as features.

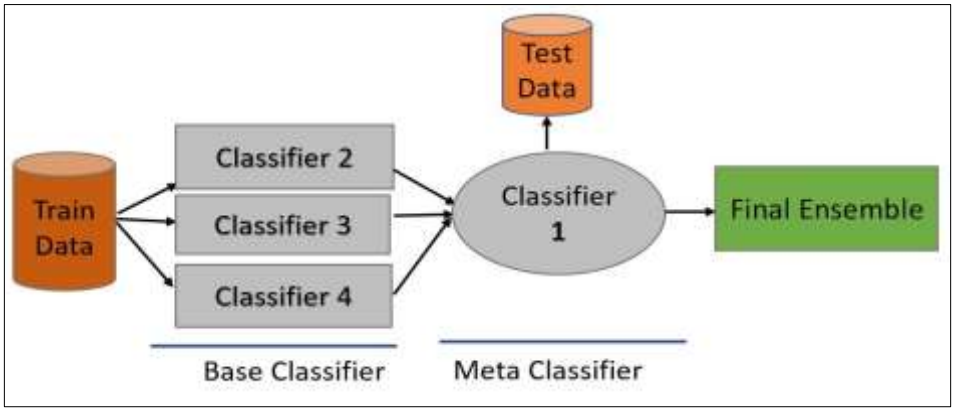

Figure 3.2: An Overview of the Stacking Classifier Framework.

To avoid revealing target data into the training set, it is critical to adhere to certain guidelines while layering classifiers. The accompanying instructions ensure that the necessary method is carried out:

Using Various Training Data for Level 1 Predictions To create level 1 predictions, it is prescribed to utilize a part of the training data that was not used in the level 1 classifier training process. To ensure that no data overlaps with the information used to train the level 1 classifier, it is desirable to choose this subset from the remaining training set.

The Training Set may be separated into the accompanying sections: It is appropriate to split the training dataset in half. The first half of the data set should be used to train the first-level classifier, and the second half should simply be used to make predictions using the classifier that has been learnt.

the meta-classifier's advancement. While training the meta-classifier, it is imperative to use the predictions created during the training of the first-level classifier immediately. This goal can be accomplished by utilizing the forecasts that are gotten from the later part of the training dataset.

It is crucial to think about cross-validation using k-folds: One procedure that can be used to get more accurate first-level predictions is k-overlay cross-validation. The training data is partitioned into k folds, with the remaining fold being used to train the first-level classifier and the first k-1 folds being applied to the remaining fold for validation. By running this process through several cycles, its stability is guaranteed.

The operational procedures shown in Figure 3.3 must be finished to uphold these regulations. In particular, the k-overlay cross-validation technique helps to increase the accuracy of predictions made in the first stage. This technique prevents target information from being incorporated during the training phase and ensures that the classifiers are layered in good shape.

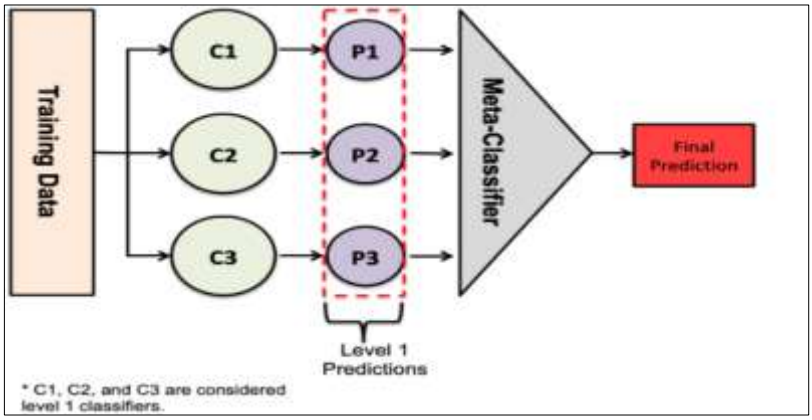

Figure 3.3: Three Separate Classifiers Make Up the Classification Stack in this Case.

Figure 3.4 shows a stacking arrangement in which the stacking structure omits an additional layer of classifiers. The stack would turn out to be significantly more perplexing if it somehow managed to be expanded, despite the fact that it would become possible to do as such.

Consider the accompanying system: classifiers are layered hierarchically over various levels or layers. The more layers added to the model, the more mind boggling it becomes, which raises the risk of overfitting and reduces the interpretability of the model. Managing and working on the performance of several classifier layers can also be challenging, particularly in real-world scenarios when time and computational resources are restricted. This statement is especially evident in circumstances that are wasteful.

As a result, it's possible that the layer's removal from the layering structure was finished on purpose to strike a compromise between the model's intricacy and performance. Despite the fact that this simplified technique isn't excessively complicated, it still benefits from layering, which includes worked on forecast accuracy and resilience.

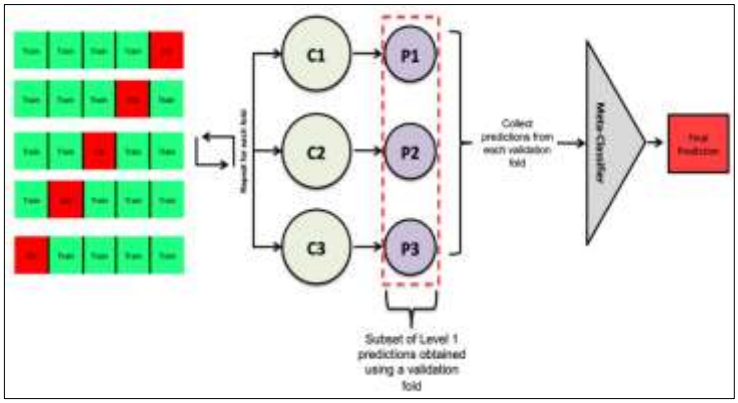

Figure 3.4: Diagram of k-Fold Cross Validation Applied to A Framework for Stacking Classifiers.

Figure 3.5 shows a representation of a stacking design that resembles a neural network. Each "neuron" is associated with a classification part. After some time, the structure starts to display traits that are similar to those of a neural network. Indeed, even while stacking and neural networks are comparable, it's memorable's important that these two approaches are totally different from each other.

The layering structure may get far additional mind boggling as additional classifiers are added, similar as in a neural network. Since it can quickly spiral crazy, management of this intricacy is absolutely necessary. Therefore, Level 2 is not expected to use the same number and kind of classifiers as Level 1. Classifiers like decision trees, additional trees, and support vector classifiers are some of the ones tracked down in the Level 1 category. The classifiers that are being examined demonstrate skill in assessing a wide variety of data kinds and learning styles.

Conversely, level 2 classifiers could be a random forest, an artificial neural network, or several different support vector classifiers. The combination of these classifiers' predictions and the predictions given by Level 1 classifiers yields the final predictions. To work on forecast accuracy and resilience, the ongoing work uses the stacking classifier design, as shown in Figure 3.5. This architecture includes countless classifiers running at various levels.

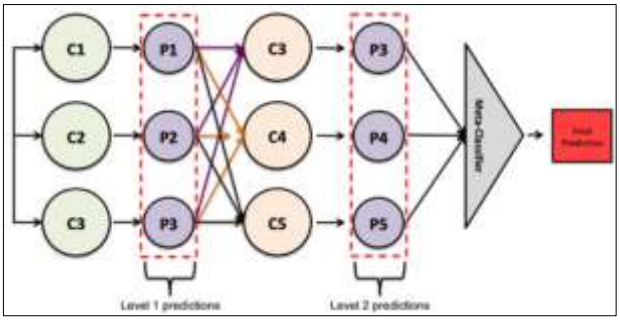

Figure 3.5: Schematic of a Stacking Classifier with two Layers of Classifiers.

3.2.4 Proposed Intrusion Detection Algorithm

Algorithm IoT IDS (Dataset.csv)

Feature_ vector ← Dataset

Label_ vector ← Dataset

[train X, test X] ← resample (Feature_vector,70%)

[train Y, test Y] ← resample(Label_vector,70%)

// Model Development

Model ← Stacking base Classifier (SVM, RF, KNN)

Model← Stacking meta-Classifier (MLP)

Trained Model ← fitc (train X, train Y)

predY ← test (Trained Model, test X)

confusion Matrix (test Y, pred Y)

[Accuracy, F-Measure] ← evaluate (testY, pred Y)

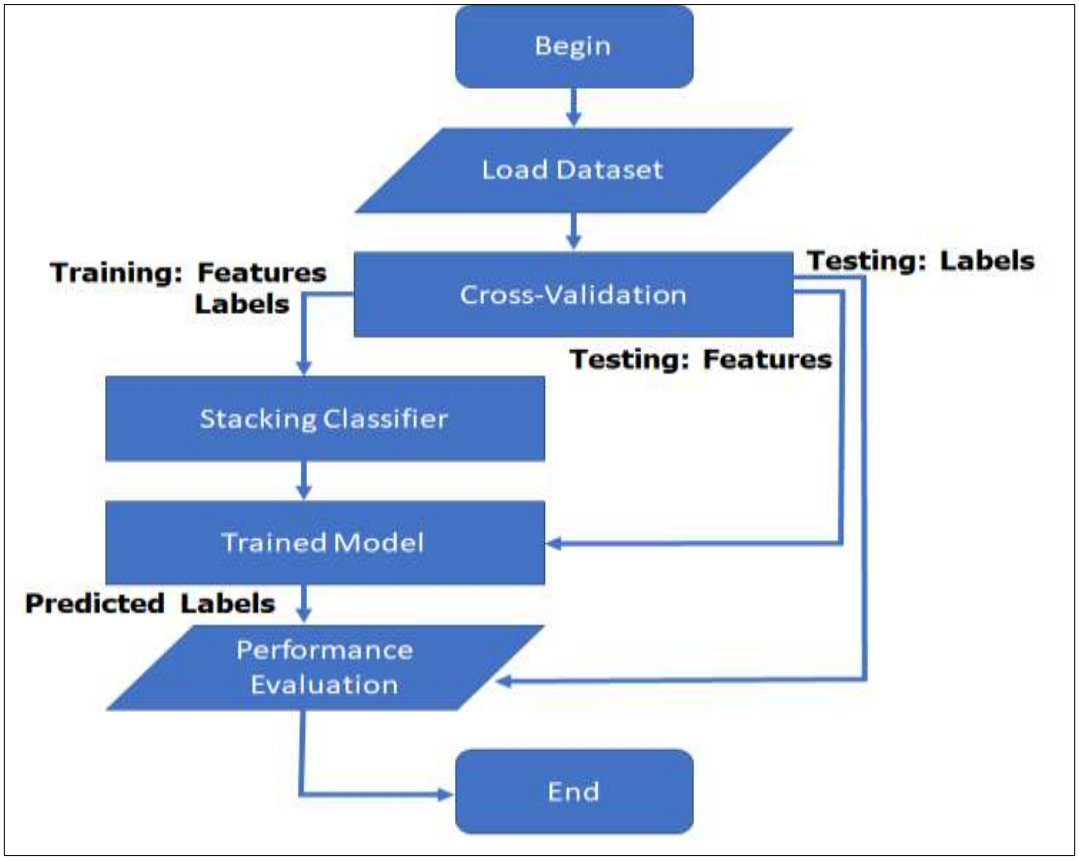

Figure 3.6: Proposed Algorithm Flow Chart.

3.3 CROSS-VALIDATION

Cross-validation, a crucial technique in the fields of data science and machine learning, splits a dataset arbitrary into two sets to evaluate a model's performance. During training, the model collects data from an assortment of features and labels to learn new things. After the training phase is north of, a validation set that includes the two features taken from the training set and real labels from the validation set is used to evaluate the model's performance.In request to evaluate the effectiveness of the training model, predictions must be made about the labels that will be used in the validation set. These predictions must then be compared to the actual labels. A confusion matrix including the variables True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) is generated by applying this approach. These are exceptionally specific guidelines for calculating performance metrics, including recall, accuracy, precision, and F-measure, among others.Additionally, K-Crease and Hold-Out cross-validation procedures are habitually used. The dataset is split into K folds of equal size to perform K-Overlap cross-validation.

Each overlay helps a training set and a validation set achieve dual resolution. With hold-out cross-validation, the dataset is split into training and test sets at a ratio of 70/30, with 70% of the data selected for training and the remaining 30% set aside for testing.

3.4 PERFORMANCE EVALUATION PARAMETERS

The performance of the suggested stacking classifier for IoT intrusion detection is assessed using the following metrics.

a. Accuracy
b. F-Measure
c. Precision
d. Recall

3.4.1 Accuracy

While discussing experimental measurements, accuracy is how much the created value closely reflects the true or anticipated value. It ascertains the measurement's degree of accuracy in relation to an officially acknowledged or accepted standard.

Conversely, repeatability and consistency in the measurements are related to precision. This demonstrates the degree of agreement between numerous measurements of the same parameter, supporting the accuracy and consistency of the experimental design.

$$\text{Accuracy} = TP+TN/TP+FP+FN+TN \quad (3.1)$$

Where TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative

3.4.2 Precision and Recall

Precision, which is sometimes alluded to as positive prescient value, is the ratio of suitable samples to all samples for which the classification indicates a positive result. It calculates how accurate the algorithm's predictions are.

Conversely, recall — also known as true positive rate — calculates the extent of relevant samples that the system accurately identifies among all the samples that were checked in the dataset. This measure analyzes the arrangement's ability to accumulate all relevant information without making any mistakes.

The recall and precision preparations are shown in Equation 3.2, allowing estimation of the performance in terms of recall (ability to gather all relevant items) and precision (ability to deliver positive, accurate predictions).

$$\text{Precision} = TP/TP+FP \tag{3.2}$$

$$\text{Recall} = TP/TP+FN \tag{3.3}$$

Where TP= True Positive, FP= False Positive, FN= False Negative

3.5 SIMULATION TOOL

The University of Waikato in New Zealand is the source of the robust graphical user interface (GUI) program MATLAB. MATLAB has strong capabilities for data mining and machine learning, including feature selection, processing, visualization, regression, and clustering. Java is the programming language that forms its basis. MATLAB version 3.8.4 was the machine learning innovation used in this analysis to categorize botnet malware from Internet of Things devices. MATLAB's large capability library and natural interface make it easier to apply different machine learning techniques and algorithms.

Comprehensive assessment data, including false-positive and false-negative rates, execution times, accuracy, confusion matrices, precision, recall, and more, can be created via MATLAB. These metrics assess the categorization model's efficacy and assist with deciding how well it detects IoT botnet malware. By using MATLAB's features, scientists can carry out tests, evaluate data, and choose how to classify IoT botnet malware in a productive manner. This commitment facilitates the detection of threats and the development of cybersecurity research.

3.5.1 Parameters for Simulation

Table 3.2: Some Parameters for Experimental Work.

Programming Language	MATLAB
Packages	Supervised Machine Learning
Datasets	BoTNeTIoT-L01
Classes	Combo, Junk, TCP, Scan, ack, syn etc.
Classifiers	Ensemble : Random Forest, MLP, SVM and KNN
Performance Evaluation Metrics	Accuracy,Precision, Recall and F-Measure

3.6 SUMMARY

The goal of this research report's author is to give readers an intensive grasp of the philosophy through the Research Technique chapter, which outlines the approaches, tactics, and designs used during the request. The importance of using reference datasets to assess intrusion detection system efficacy for the Internet of Things is emphasized heavily. To support the judgments that were made, this chapter provides an analysis of the chosen designs and procedures, illustrating their advantages and disadvantages in relation to the study objectives. This study primarily uses an experimental request approach. Controlled experiments are used to evaluate intrusion detection systems planned for the Internet of Things. One of the many benefits of experimental research is its ability to decide the causal links between variables, which can give important information about the effectiveness of various intrusion detection techniques. The research may also remember creative approaches for addition to experimental studies to give a comprehensive version of the datasets and hardware included. Descriptive research uses methodical data assortment and analysis to shed light on particular characteristics. Using this strategy may have the advantage of making the research atmosphere easier to create and aiding in scene preparation.

4. RESULTS AND DISCUSSION

4.1 INTRODUCTION

This segment gives a definite assessment of the exploratory discoveries that were found by a careful assessment and conversation of the impersonations made on the objective dataset. These were the objectives for which the examinations were planned. The IoT Botnet dataset is separated into seven classes: Combo, Garbage, Output, TCP, UDP, UDP Plain, and Ack. Every one of these modules satisfies a specific capability.

The recommended approach is executed with the assistance of the MATLAB programming, a notable exploration recreation device intended for text and information extraction. MATLAB is notable for its refined elements. By utilizing the MATLAB bundle the board, clients might get the latest bundles made by the MATLAB improvement group and other examination gatherings. In light of its easy-to-use interface and the overflow of AI and information science calculations coordinated in Java, MATLAB is unquestionably accessible to clients with many foundations. This accessibility decreases the requirement for incredibly high programming abilities while working with trial and error and further developing the client experience.

A 3.7 GHz Center i7 workstation, 16 gigabytes of random-access memory (RAM), and a 4 GB graphics processing unit (GPU) are completely remembered for the PC utilized for the preliminaries. Along these lines, the exhibition of laid out processes with and without checking is painstakingly contrasted all together with determine the adequacy of the proposed technique. This examination gives adroit data on the viability of the arrangement.

4.2 IOTML1

The KNN classifier in this stacking classifier, which is called the IoTML1, serves as a meta classifier, while the SVM, MLP, and RF classifiers serve as base classifiers. This stacking classifier was the first suggested one.

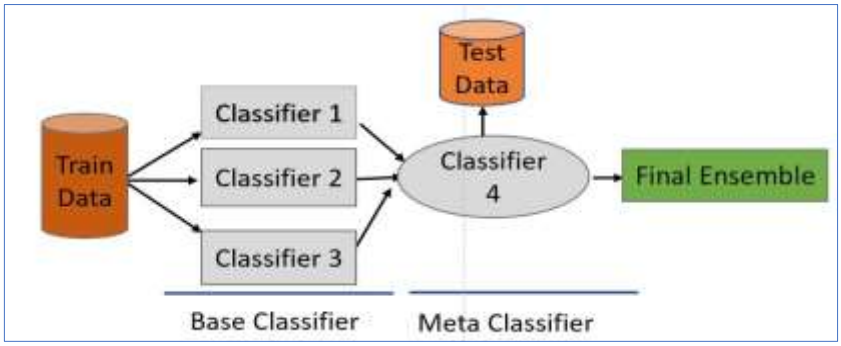

Figure 4.1: Architecture for the IoTML1 Stacking Ensemble Classifier That Has Been Proposed.

The result of the IoTML1 model's thorough quality examination is displayed in table 4.1 of the going with realistic (see Table 4.1). The cells that have been precisely ordered by the size prerequisites are displayed in the accompanying table (green cells). The red cells that are absent from different spots are additionally shown alongside it.

Accordingly, the pre-owned strategy was effective in expanding exactness by lessening the known gamble that much of the time happens to group techniques. Thinking about this, the model will without a doubt expand the forecast's worth since it can consolidate most events, like those displayed in the table as green.

The correlation showed the trustworthiness of the outfit approach utilized in the IoTML1. The method brought about a more dependable classifier, which further developed test accuracy and diminished the probability of misclassifications. The proposed method's exhibition has been completely analyzed measurably, and it is guessed that future IoT frameworks would expect it to be safer.

Table 4.1: A Confusion Matrix for The Ensemble Classifier Iotml1.

	Combo	*Junk*	*Scan*	*TCP*	*UDP*	*UDP-Plain*	*Ack*
Combo	*1136*	*0*	*0*	*0*	*0*	*0*	*0*
Junk	*0*	*485*	*0*	*0*	*0*	*0*	*0*
Scan	*0*	*0*	*857*	*0*	*0*	*0*	*0*
TCP	*0*	*0*	*0*	*1240*	*0*	*0*	*1*
UDP	*0*	*0*	*0*	*0*	*1937*	*0*	*0*
UDP-Plain	*0*	*0*	*0*	*0*	*0*	*922*	*0*
Ack	*0*	*0*	*0*	*0*	*0*	*0*	*2484*

To figure out which spots of the utilized artificial intelligence frameworks were disconnected, Table 4.2 presentations the exactness, review, and F-measure that were accounted for with the table. In this occurrence, preparing the models under conditions that give adequate execution by considering different perspectives is a fundamental piece of the legitimate appraisal.

The model can achieve up to 100 percent of a perfect mean ten years, as exhibited by this outcome, showing really astonishing execution and insignificant misfortunes as the primary driver for concern. The model can precisely deduce the presence of stowed away examples and qualities inside the information with this degree of exactness. This proposes that the model has an exceptionally serious level of consistency, which converts into very precise expectations.

Moreover, the utilization of this model raises the worth of the F-measure by showing that, in contrast with prior times when people needed such complex colleagues, individuals today deal with their connections on a far lower social level. The model is valuable since it very well may be applied really in various situations and on the grounds that it can resolve issues with the IoT framework for which it was expected, meanwhile improving the f measure, which fills in as a check of the model's quality. As shown by the model's flawlessness in a few measurements and capacity to forestall predisposition, Table 4.2 validates the model's solidarity and capacity to deal with the example size that the biggest informational index normally contains. The model being talked about, rather than numerous others, shows that applications roused by the Web of Things idea may be sent without forfeiting productivity, despite the fact that the subject is as yet argumentative.

Table 4.2: Comprehensive Evaluation of Iotml1 Ensemble Classifier Performance by Class.

Class	*TP Rate*	*FP Rate*	*Precision*	*Recall*	*F-Measure*
Combo	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
Junk	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
Scan	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
TCP	*0.99*	*0.00*	*1.00*	*0.99*	*1.00*
UDP	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
UDP-Plain	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
Ack	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
Average	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*

A general design of the all out number and rate relating to the characterization discoveries of right and wrong examples is displayed in Table 4.3. The model has a noteworthy typical precision of 99.98%, which is outstanding. This pattern is found in the 9062 events in the example when there is only one misclassification. The model successfully catches the information as proven by its ability to segregate between classes as shown by the forecast exactness. Nonetheless, various measurable appraisal measurements, for example, root mean square blunder, kappa insights, and relative outright mistake, likewise support the legitimacy of the proposed model. By contrasting the model results with a foreordained worth, you might represent the model's exhibition and give additional extension to their unwavering quality assessment. Table 4.3 presents the recommended AI model as a completely execution tried model, including an extensive variety of assessment rules. The model's versatility and adequacy in precisely anticipating results through characterizations are fortified by the back to back satisfaction of good exactness with the achievements of other assessment methods. One more consequence of the model's ability to accomplish high precision regarding honesty is represented around the table, so reinforcing the possibility that it could be utilized to true IoT interruption identification situations.

Table 4.3: Statistical Quantitative Analysis in IoTML1.

Correctly Classified Instances	*9061*	*99.98%*
Incorrectly Classified Instances	*1*	*0.01*
Kappa Statistic	*0.99*	
Mean Absolute Error	*0.00*	
Root Mean Square Error	*0.00*	
Relative Absolute Error	*0.03%*	
Root Relative Squared Error	*1.63%*	

4.3 IOTML2

At first, the "Internet of Things Machine Learning 2" (IoTML2) model was recommended as the classifier for this specific case. The fundamental classifiers Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Timberland are among the pieces that characterize the framework. The meta-classifier itself has three layers in the layering framework notwithstanding MLP hypothesis. By giving information, the stacking method capabilities as the joined result for the SVM, KNN, and RF calculations. To accomplish the last expectation, the MLP remolds every one of the anticipated qualities into an info vector and afterward joins them.

IoTML2 plans to work on the viability and strength of interruption recognition for Internet of Things (IoT) frameworks using various base classifiers and a meta-classifier to consolidate the different results from these classifiers. Utilizing this strategy, it is feasible to definitively evaluate the presentation of various classifiers on a specific dataset to decide how well they empower the informational index to recognize perplexing examples. In light of everything, the IoTML2 separates itself in the interruption location area by ensuring the utilization of classifiers in layers to accomplish the target of acquiring improved results than those that might emerge from the utilization of straightforward classifiers freely from each other. IoTML2 will actually want to recognize the bleeding edge of advancement diagram and discipline the IoT security and interruption discovery strategies by utilizing SVM, KNN, RF, and MLP classifiers.

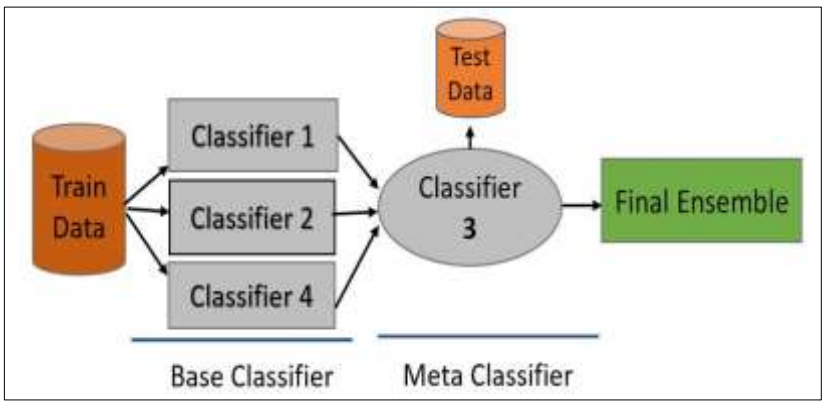

Figure 4.2: The Iotml2 Stacking Ensemble Classifier's Suggested Design.

A thing by-thing sum examination completed on the IoTML1 model is the funder examination displayed in table 4.4. Green spots demonstrate models that the model precisely named and addressed, though red dabs show models that the model erroneously classed or misdiagnosed.

By bringing down the misfortune through the strategy proposed, gatherings have been demonstrated to be less errorful, showing that it has worked on the estimation's accuracy as found through testing. The estimate of the positive circumstances, which are caught by the green parts, loans confidence to this model. It is obvious from prior discoveries that the troupe approach utilized in IoTML1 is essential, and that the basic technique enormously upgrades precision and decreases mistakes related with interruption identification. The results of the scientists' far-reaching quantum concentrate on show that the proposed system has a decent possibility giving incredible security and steadfastness to Internet of Things gadgets.

Table 4.4: A Confusion Matrix for the Ensemble Classifier Iotml1.

	Combo	*Junk*	*Scan*	*TCP*	*UDP*	*UDP-Plain*	*Ack*
Combo	*1136*	*0*	*0*	*0*	*0*	*0*	*0*
Junk	*0*	*485*	*0*	*0*	*0*	*0*	*0*
Scan	*0*	*0*	*857*	*0*	*0*	*0*	*0*
TCP	*0*	*0*	*0*	*1241*	*0*	*0*	*0*
UDP	*0*	*0*	*0*	*0*	*1937*	*0*	*0*
UDP-Plain	*0*	*0*	*0*	*0*	*0*	*922*	*0*
Ack	*0*	*0*	*0*	*0*	*0*	*0*	*2484*

Table 4.5 deals with the lopsided dataset by propelling the model approval process with accuracy, review, and F-measure (a symphonies mean of accuracy and review estimation). With this kind of study, a dataset's properties are utilized to lay out the model's viability. The model that yields a typical deficiency of 100 percent is an extra portrayal of the model, connoting immaculate accuracy and little misfortune. Their model deciphers information examples and attributes quite well, which at last outcomes in a satisfactory gauge, thanks to its high precision. Thus, the F measure, which shows the IoT examination, additionally rises. The model is currently a suitable application in the given area since it has been shown to be proficient in the F-measure improvement.

Table 4.5 exhibits that the model is effective and versatile generally speaking across a scope of execution rules, showing its capacity to work even within the sight of a lopsided dataset. The outcomes exhibit how the acknowledged approach might improve these applications and help with IoT designing and progress.

Table 4.5: IoTML2 Ensemble Classifier Performance Study Broken Down Per Class in Detail.

Class	***TP Rate***	***FP Rate***	***Precision***	***Recall***	***F-Measure***
Combo	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
Junk	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
Scan	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
TCP	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
UDP	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
UDP-Plain	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
Ack	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
Average	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*

The data provided explains the discoveries displayed in Table 4.6, which records various pointers connected with the adequacy of arrangement. Information on the all out number of tests, the level of accurately arranged examples, and the level of wrongly grouped examples are displayed in the table. The model's dumbfounding mean precision of 99.98 percent filled in as a striking illustration of its remarkable exhibition. Just a single example — out of 9062 examples — was mistakenly sorted, showing the model's remarkable precision in situational characterization. To assess the recommended model, other measurable evaluation strategies were utilized notwithstanding relative outright blunder, kappa measurements, and root mean square mistake. These procedures help in a superior understanding of the model's exactness and constancy by contrasting the model's outcomes and foreordained values.

Table 4.6: Statistical Quantitative Analysis of IoTML1.

Correctly Classified Instances	*9060*	*100%*
Incorrectly Classified Instances	*0*	*0*
Kappa Statistic	*1*	
Mean Absolute Error	*0.00*	
Root Mean Square Error	*0.00*	
Relative Absolute Error	*0.45%*	
Root Relative Squared Error	*1.49%*	

4.4 IOTML3

An illustration of the stacking classifier utilized in the first work is the IoTML3. A few instances of essential classifiers that are utilized to tackle grouping issues are SVM, KNN, and MLP. These classifiers include it. Besides, while the stacking configuration is incorporated, the RF classifier will go about as the meta classifier.

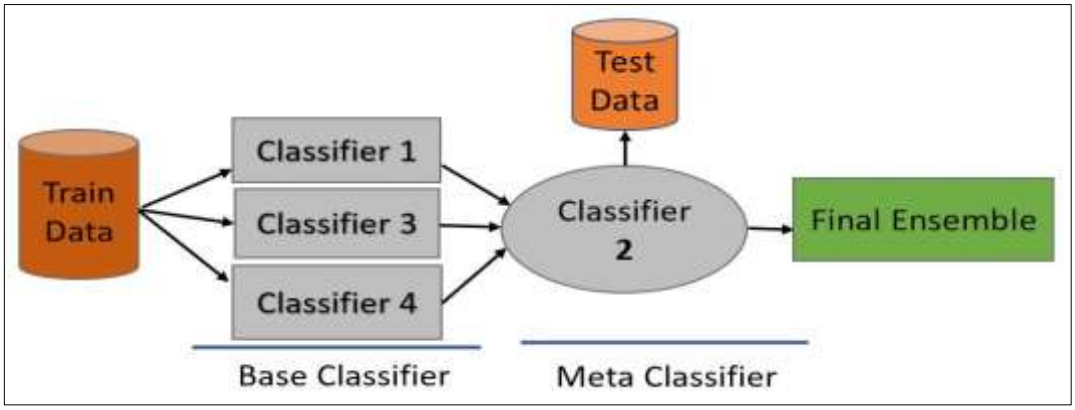

Figure 4.3: Architecture for the IoTML3 Stacking Ensemble Classifier that is Suggested.

Table 4.7 gives an itemized investigation of the amount examination performed on the recommended model IoTML1. Cases that were inappropriately ordered are addressed by the qualities in red boxes, and cases that were accurately grouped along the corner to corner are addressed by the qualities in green cells. The consequences of the analysis show that the recommended procedure further developed exactness by decreasing the misfortunes that happened during the group strategy. This shows how well the model works to further develop order precision and decrease misclassifications.

Table 4.7: IoTML1 Ensemble Classifier's Confusion Matrix.

	Combo	*Junk*	*Scan*	*TCP*	*UDP*	*UDP-Plain*	*Ack*
Combo	*1136*	*0*	*0*	*0*	*0*	*0*	*0*
Junk	*0*	*485*	*0*	*0*	*0*	*0*	*0*
Scan	*1*	*0*	*856*	*0*	*0*	*0*	*0*
TCP	*0*	*0*	*0*	*1239*	*0*	*1*	*1*
UDP	*0*	*0*	*0*	*0*	*1937*	*0*	*0*
UDP-Plain	*0*	*0*	*0*	*0*	*0*	*922*	*0*
Ack	*0*	*0*	*0*	*0*	*0*	*0*	*2484*

Attributable to the lopsided conveyance of the dataset, Table 4.8 presents the approval of similar model utilizing numerous exhibition rules, (for example, review, f-measure, and exactness). This technique empowers the assessment to take into account the dataset's particular elements enough.

This method delivered the best outcomes concerning exactness and effectiveness misfortune for a supported classifier. Thus, whether or not this model will find success can be settled on

the off chance that the mean score for each model is 100 percent. Moreover, a better f-measure was accomplished; thus, the model is appropriate for utilization in Internet of Things or shrewd city applications. Subsequently, this is supported by the way that it is vital to the IoT frameworks' overhauls using innovation, to be specific.

Table 4.8: Comprehensive Evaluation of IoTML3 Ensemble Classifier Performance by Class.

Class	*TP Rate*	*FP Rate*	*Precision*	*Recall*	*F-Measure*
Combo	*1.00*	*0.00*	*0.99*	*1.00*	*1.00*
Junk	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
Scan	*0.99*	*0.00*	*1.00*	*0.99*	*0.99*
TCP	*0.99*	*0.00*	*1.00*	*0.99*	*0.99*
UDP	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
UDP-Plain	*1.00*	*0.00*	*0.99*	*1.00*	*0.99*
Ack	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
Average	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*

The complete number of tests that were submitted to the scientific lab is displayed in the last segment of Table 4.9. Moreover, a rate section illuminates us regarding the examples that were accurately and inaccurately perceived. With a typical exactness of simply 0.02%, the model might be viewed as especially high since it just ordered one out of 9062 examples wrong. Moreover, I decide to utilize root mean square blunder, kappa measurements, and relative outright mistake as the techniques to check the legitimacy of my recommended model. These methodologies work on the model's exhibition in order situations by empowering the model's presentation to be contrasted with preset benchmarks.

Table 4.9: IoTML1 Quantitative Statistical Analysis.

Correctly Classified Instances	*9059*	*99.96%*
Incorrectly Classified Instances	*3*	*0.03*
Kappa Statistic	*0.99*	
Mean Absolute Error	*0.00*	
Root Mean Square Error	*0.00*	
Relative Absolute Error	*9.47%*	
Root Relative Squared Error	*25.19%*	

4.5 IOTML4

With regards to this review, the first stacking classifier recommended was the IoTML1. The basic classifiers in this framework are the KNN, MLP, and RF classifiers. As another option, the SVM classifier is responsible for doing the obligations of the meta classifier.

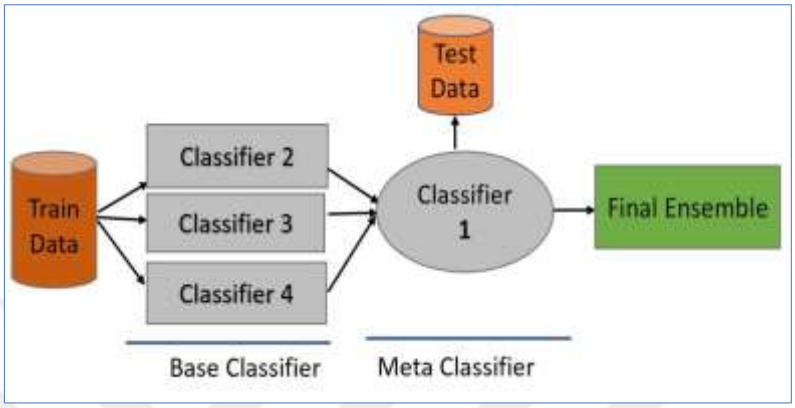

Figure 4.4: The IoTML4 Stacking Ensemble Classifier's Suggested Design

Table 4.10 presents a careful quantitative assessment of the proposed model IoTML1. Mistakenly arranged occasions are shown by red cells, while accurately ordered occurrences are demonstrated by green cells on the inclining. The examination's discoveries show that the proposed system effectively expanded exactness by diminishing the misfortune associated with the troupe strategy.

Table 4.10: A Confusion Matrix for The Ensemble Classifier IoTML1.

	Combo	*Junk*	*Scan*	*TCP*	*UDP*	*UDP-Plain*	*Ack*
Combo	*1136*	*0*	*0*	*0*	*0*	*0*	*0*
Junk	*1*	*484*	*0*	*0*	*0*	*0*	*0*
Scan	*0*	*0*	*857*	*0*	*0*	*0*	*0*
TCP	*0*	*0*	*0*	*1241*	*0*	*0*	*0*
UDP	*0*	*0*	*0*	*0*	*1937*	*0*	*0*
UDP-Plain	*0*	*0*	*0*	*0*	*0*	*922*	*0*
Ack	*0*	*0*	*0*	*0*	*0*	*0*	*2484*

The skewness of the dataset is taken into account during model approval. Table 4.11 gives an assortment of execution measurements, for example, f-measure, review, and exactness, to assist with accomplishing this. A raised f-measure showing the tendency towards Internet of Things (IoT) applications features the viability of the model even at 100 percent by and large, exhibiting remarkable precision with little wearing down.

Table 4.11: Comprehensive Evaluation of IoTML4 Ensemble Classifier Performance by Class.

Class	*TP Rate*	*FP Rate*	*Precision*	*Recall*	*F-Measure*
Combo	*1.00*	*0.00*	*0.99*	*1.00*	*1.00*
Junk	*0.99*	*0.00*	*1.00*	*0.99*	*0.99*
Scan	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
TCP	*0.99*	*0.00*	*1.00*	*0.99*	*1.00*
UDP	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
UDP-Plain	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
Ack	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*
Average	*1.00*	*0.00*	*1.00*	*1.00*	*1.00*

The all-out number of tests and the rates of accurately and erroneously perceived examples are displayed in Even 4.12. Across 9062 examples, the model's typical exactness was 99.98%, with only one case of wrong distinguishing proof. To think about the proposed model in contrast to known values, measurable evaluation approaches such kappa measurements, relative outright blunder, and root mean square mistake are additionally used.

Table 4.12: IoTML1 Quantitative Statistical Analysis

Correctly Classified Instances	*9061*	*99.98%*
Incorrectly Classified Instances	*1*	*0.01*
Kappa Statistic	*0.99*	
Mean Absolute Error	*0.00*	
Root Mean Square Error	*0.00*	
Relative Absolute Error	*86.89%*	
Root Relative Squared Error	*87.87%*	

A reference diagram contrasting the viability of a few stacking order techniques using IoT botnet information is displayed in Figure 4.5. That's what the diagram shows, when it came to distinguishing various sorts of IoT interruption dangers, IoTML2 was the most reliable, while IoTML3 was the most un-exact. The outcomes displayed here struggle with those got for IoTML4.

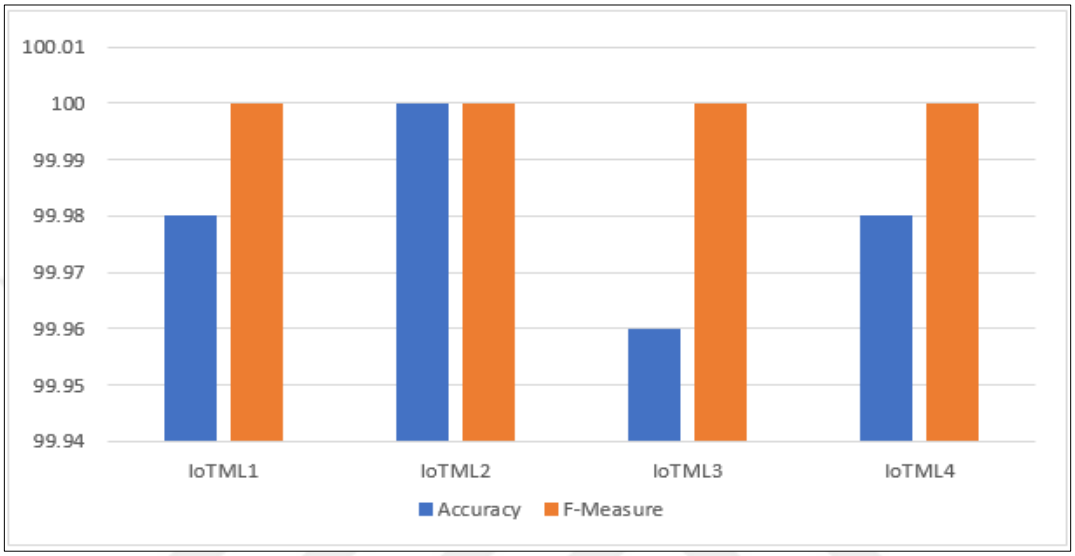

Figure 4.5: Comparing the Performance of Different Ensemble Learners.

4.6 PROPOSED MODEL COMPARISON WITH STATE-OF-THE-ART

This part presents a correlation investigation of the cutting-edge research distributed on the benchmark dataset with the exploratory consequences of the proposed model. These superb pieces go about as benchmarks, exhibiting the ongoing degree of progress. Both the proposed model and the model recommended by a subsequent creator are approved utilizing the IoT Botnet Dataset. In view of accuracy, proficiency, and low weight, the outcomes show that the recommended model works better compared to the substitute. The superior exactness of the proposed model features its convenience and viability in Internet of Things organizations, supporting security.

Table 4.13: The Most Sophisticated Models and The Suggested Intrusion Detection System Model are Compared.

No.	Dataset	Method	Accuracy
1	Botnet	DNN	94.0%
2	Botnet	Neural Network	99.02%
3	Botnet	CNN+LSTM	90.88%
4	Botnet	Proposed Model	100%

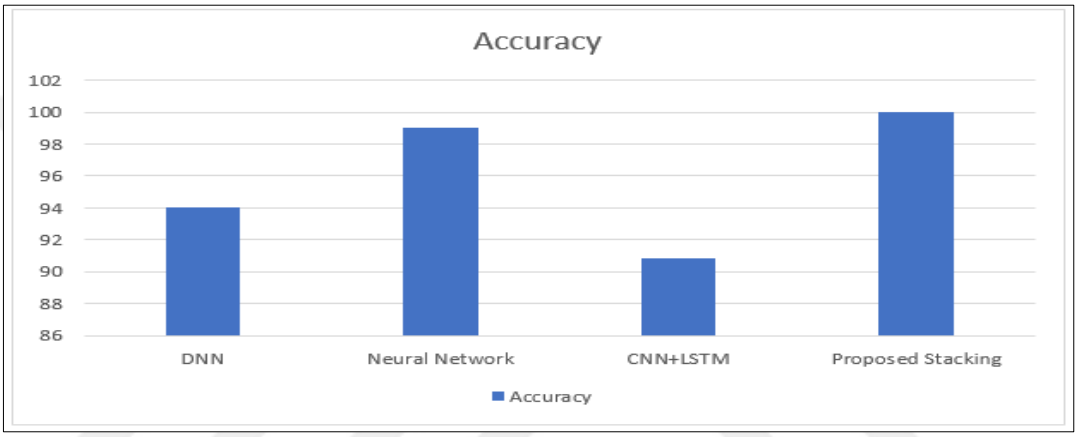

Figure 4.6: The Suggested Ensemble Learner's Accuracy in Comparison to Other Cutting-edge IDSs.

4.7 SUMMARY

The outcomes of reworking base and meta classifiers to utilize four stacking classifiers as opposed to one are examined in the Synopsis of Results and Conversation section. The proposed worldview for the production of interruption discovery frameworks is reliable and compelling, as indicated by trial information.

The best model might be picked by looking at the precision consequences of the four IoTML models. The exhibition factors and benefits and weaknesses of each model are displayed in this examination study.

Also, the most encouraging model is diverged from the latest Botnet IoT dataset research. To all the more likely figure out the model's exhibition and recognize regions for advancement, it is contrasted with before research.

The stacking classifiers and their effect on IoT interruption recognition are completely assessed in the part named "Outline of Results and Conversation." Through top to bottom review and examination, this segment features the capability of the recommended models and adds to the field of network safety and IoT security research.

5. CONCLUSION AND FUTURE RECOMMENDATION

5.1 CONCLUSION

The current task includes the examination and development of a framework that can perceive an assortment of IoT penetration risks consequently. Four classifiers are utilized in the troupe stacking classifier-based model. Base classifiers make of three of the classifiers, while a fourth classifier marks IoT information to recognize protected and perilous movement.

Independent IoT interruption identification frameworks utilizing machine learning based order dependably and quickly identify and classify IoT attacks. Highlights that are taken out of an encoding plan are utilized by machine learning models to prepare and self-approve. The dataset is parted 70-30 for preparing and testing by the holdout strategy.

Botnet attack identification is almost 100 percent improved when many layered arrangement plans are utilized. A relative examination with the latest IDS frameworks shows that the proposed design perceives botnet-based attacks and may develop with extra motors to tackle new dangers.

MATLAB is utilized to recreate the proposed procedure, which empowers complete model approval and evaluation. Through fastidious testing and examination, the review shows the adequacy and steadfastness of the recommended IoT interruption recognition framework, further developing IoT security and online protection research.

5.2 CONTRIBUTION

The methodology for building an intrusion detection system (IDS) utilizing machine learning strategies — all the more particularly, support and managed learning — is introduced in this postulation. To work with the acknowledgment of dangers that have previously been perceived, this system endeavors to gauge the force of known and unknown kinds of cyberattacks.

To track down the best model for expectation at a specific level and to explore the objective class order, this strategy makes utilization of knowledge models and progressive grouping. This technique makes sure that exhibition is at its best by picking the best model for every expectation level.

We utilize models to conjecture the seriousness of uncommon attack types for which there isn't sufficient preparation information. By giving network supervisors data on attack types that have the most noteworthy likelihood of happening, these models further develop independent direction.

The knowledge-based various leveled intrusion detection system (IDS) accomplishes ideal scores of 100 percent in F-measure, precision, and review, beating existing cutting edge methods. The remarkable outcome might be credited to the strategy's ability to get perfect scores and proficiently address novel attack classes by utilizing expected seriousness and data archived in the knowledge model.

In addition, this technique gives exhaustive data on the extension and force of attacks, empowering network supervisors to make taught choices. It is trusted that by including systems for picking up new attacks and refining model retraining spans, the methodology will turn out to be all the more progressively learning in ensuing examinations. Deciding the best chance to retrain models will be the primary objective of future endeavors to resolve this issue.

5.3 FUTURE RECOMMENDATIONS

The review's decisions highlight spots where the recommended recognizable proof strategy performs well, yet there is still opportunity to get better. The aftereffects of this examination highlight one-of-a-kind dissemination designs in IoT network highlights, which might be utilized to further develop intrusion attack detection. To achieve a serious level of safety, it is intended to examine strategies for integrating the recommended technique into genuine equipment and software answers for the Internet of Things (IoT). Since hash table matching is intrinsically equal, using equal processing —, for example, graphics processing units (GPUs) — can work on working effectiveness and empower continuous applications. Regardless of whether the proposed approach performs well, it might yet be reinforced. It is noticed that specific IoT information tests are erroneously recognized by the methodology, regardless of whether it creates discernibly further developed brings about spotting IoT odd attacks. To tackle this issue, we are thinking about the reconciliation of advantageous elements, including those acquired through the utilization of profound learning calculations for highlight extraction. When contrasted with other state of the art draws near, profound

learning strategies — specifically, Convolutional Neural Networks (CNNs) for include extraction — offer higher precision. One more method for expanding the precision of IoT intrusion attack detection systems is to involve profound learning procedures for arrangement, to be specific Recurrent Neural Networks (RNNs) built on Long Short-Term Memory (LSTM) layers. By adding RNNs to the system, we can take utilization of their modern highlights for relapse and grouping, which will further develop the intrusion detection system's exhibition and precision significantly further. These advancements can tackle current issues and essentially work on the adequacy of IoT safety efforts.

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APPENDIX A

SIMULATION CODE

```
% Converting BoT-IoT to spectrogram images

Features = Features(1:3000,:);

for i = 1:3000

    N = 1024;

    n = 0:N-1;

     w0 = 2*pi/5;

    x = Features(i,:);

    s = spectrogram(x);

    % Plot and save the spectrogram

    figure;

    spectrogram(x, 'yaxis');

    title('Spectrogram');

    xlabel('Time');

    ylabel('Frequency');

    colormap('jet'); % Adjust colormap as desired

     % Define filename and path

    filename = sprintf('spectrogram_%d.png', i); % Include index in filename

    filepath = fullfile('C:\Users\Muhammad Shoaib\Desktop\Junaid111\Dyna Code\Dataset\images', filename);
```

```
    % Save the spectrogram image
    saveas(gcf, filepath);
    fprintf('Spectrogram image %d saved to: %s\n', i, filepath);
    close(gcf); % Close the figure to avoid display
end
```

A.1 Proposed Classification Code

```
% load('Dataset'); %Load the dataset
featuress = selected_features; %save the features from P
labels = selected_labels; %save the labels from T
 %%
%Cross-Validation: Splitting the dataset into a trainset and testset
n = length(labels); %calculate the number of total samples
cvp = cvpartition(n,'Holdout',0.3) %splitting the data with 70% training and 30% testing
trainX = featuress(cvp.training,:); %Selecting the 70% of features
testX = featuress(cvp.test,:); %Selecting the 30% of features
trainY = labels(cvp.training,:); %Selecting the 70% of labels
testY = labels(cvp.test,:); %Selecting the 30% of labels
 %%
svmModel = fitcknn(trainX, trainY);
knnModel = fitcknn(trainX, trainY);
```

```
treeModel = fitctree(trainX, trainY);

%%

% Predictions on test data

svmPred = predict(svmModel, testX);

knnPred = predict(knnModel, testX);

treePred = predict(treeModel, testX);

% Create the ensemble by combining predictions

ensemblePred = mode([svmPred, knnPred, treePred], 2);

 % Evaluate the ensemble model

accuracy = sum(ensemblePred == testY) / numel(testY);

fprintf('Ensemble Accuracy: %.2f%%\n', accuracy * 100);

%%

C = confusionmat(testY, ensemblePred);

figure

confusionchart(C, unique(testY), 'Title', 'Confusion Matrix');

%%

[~, scores] = predict(ensemblePred, testX);

labels = unique(testY);  % Unique class labels in your test data

 % Initialize arrays to store TPR and FPR values

TPR = zeros(length(labels), length(labels));
```

```
FPR = zeros(length(labels), length(labels));
 % Initialize an array to store AUC values
AUC_values = zeros(length(labels), 1);
 % Calculate TPR and FPR for each class
for i = 1:length(labels)
    class_label = labels(i);
    class_scores = scores(:, i);
        % Sort scores in descending order
    [sorted_scores, sort_idx] = sort(class_scores, 'descend');
    sorted_labels = testY(sort_idx);
        % Initialize TP and FP counts
    TP = 0;
    FP = 0;
        % Calculate TPR and FPR
    for j = 1:length(sorted_labels)
        if sorted_labels(j) == class_label
            TP = TP + 1;
        else
            FP = FP + 1;
        end
```

```
        TPR(i, j) = TP / sum(sorted_labels == class_label);
        FPR(i, j) = FP / sum(sorted_labels ~= class_label);
    end
 % Calculate AUC for each class
AUC_values(i) = trapz(FPR(i, :), TPR(i, :));
end
% Plot ROC Curve
figure
for i = 1:length(labels)
 plot(FPR(i, :), TPR(i, :), 'LineWidth', 1.5);
 hold on;
end
% Create legends with class labels and AUC values
legendLabels = cell(length(labels), 1);
for i = 1:length(labels)
legendLabels{i} = sprintf('Class %d (AUC = %.2f)', labels(i), AUC_values(i));
end
legend(legendLabels, 'Location', 'southeast');
xlabel('False Positive Rate (FPR)');
ylabel('True Positive Rate (TPR)');
```

```
title('ROC Curve for Multiple Classes');

hold off;

%%

C = confusionmat(testY, ensemblePred);

numClasses = size(C, 1);

precision = zeros(numClasses, 1);

recall = zeros(numClasses, 1);

f1Score = zeros(numClasses, 1);
```