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An Efficient Concrete Compressive Strength Prediction Method Based Recurrent Neural Network and Particle Swarm Optimization Algorithm

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An Efficient Concrete Compressive Strength Prediction Method Based Recurrent Neural Network and Particle Swarm Optimization Algorithm

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The thesis titled “AN EFFICIENT CONCRETE COMPRESSIVE STRENGTH PREDICTION METHOD BASED RECURRENT NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION ALGORITHM” prepared and presented by “Abdualmeer Sabbar KOKAZ ” was accepted as a Master of Science Thesis in Information Technologies.

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Abdualmeer Sabbar KOKAZ

DEDICATION

First, I would like to thank Allah Almighty for the power of the mind, health, strength, guidance, knowledge, and skills to complete this study.

This thesis is wholeheartedly dedicated to my parents. There are no words to describe what you mean to me; there is nothing that I can repay for what you have done to me. I will continue to do my best to achieve your expectations.

Lastly, I dedicated this to the family, relatives, and friends who have been encouraging me during this study.

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ABSTRACT

An Efficient Concrete Compressive Strength Prediction Method Based Recurrent Neural Network and Particle Swarm Optimization Algorithm

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One of the greatest dangerous parameters in concrete project is compressive strength. As the compressive strength of concrete is properly slow, cost and time can be reduced. Concrete strength is comparatively hardy to influences on the situation. The manufacture of concrete compressive strength is importantly predisposed by severe climate environments and growths in moisture rates. In this study, efficient method presented combined RNN with PSO to predicate the Concrete Compressive Strength. The proposed method compared with two classical methods neural network and naïve bayes classifier. The proposed method presented best results than classical techniques when several metric parameters are compared such as mean error, mean squared error, mean percentage error, and root mean squared error.

Keywords: Concrete compressive strength, RNN, Optimization algorithms, PSO.

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LIST OF ABBREVIATIONS

RNN	:	Recurrent Neural Network
PSO	:	Particle Swarm Optimization Algorithms
DL	:	Deep Learning
GA	:	Genetic Algorithm
ACO	:	Ant Cony Optimization

1. INTRODUCTION

High performance concrete (HPC) is used in the construction of strategically important structures (nuclear power plants, dams, military facilities, etc.). With the modern construction and chemical infrastructure used today, studies to increase the strength of this building material are increasingly continuing. Normally concrete; cement, aggregate and water; are combined in appropriate proportions. HPCs, on the other hand, need some additions to increase their strength and reduce the vulnerabilities of normal concrete. The strength values of the material can be increased/decreased by changing the mixing ratios of these additives. Many experiments are required to obtain the mixture ratio that will provide maximum strength. If these experiments are performed in a laboratory environment, a large amount of equipment, labor and financial resources will be required, and all these cost and labor losses can be prevented by using previously obtained data and successfully tested machine learning methods.

In this study; The usability of Support Vector Machines (SVM), which combines various techniques from statistics, machine learning and neural networks, and Artificial Neural Networks (ANN), which is inspired by the information processing function by simulating the functioning of the biological nervous system of the human brain, in estimating the axial compressive strength of high-performance concrete. investigated and the results obtained by these two methods were compared.

In the study, the concrete strength data set [1] of 1030 samples, which were made in 17 different laboratories, were analyzed by SVM and ANN methods, and as a result of the estimations made with these two methods; It has been seen that SVMs give more satisfactory results in terms of consistency and predictive power. In recent years, studies on concrete strength estimation using different methods and data sets have gained momentum.

It has been observed in the literature that ANNs are widely used for the estimation of concrete compressive strength [2-8]. Yeh [2] showed that ANNs can be used as an effective method in the estimation of concrete strength, and showed that much higher estimation success can be achieved with ANNs than with regression analysis. A similar study was done by Atici [9]. The author reported the superiority of ANNs in his study in which he compared the estimation results of ANN with multiple regression analysis. Comparing the prediction success of self-organization feature map (SOFM), which is an ANN model, with multiple regression analysis, Nikoo et al. [10] reported the superiority of SOFM. Fazel-Zarandi et al. [11] proposed a fuzzy polynomial neural network model consisting of a combination of fuzzy neural networks and polynomial neural networks for the prediction of concrete strength. Yeh and Lien [12] Decision tree (operation tree) and genetic algorithms for HPC compressive strength estimation.

Although SVMs are widely used in many civil engineering studies such as project cost [13] and project completion time estimation [14], their application in concrete strength estimation is limited. Cheng et al. [15] Evolutionary fuzzy support vector machine inferential model for time series data, which is a hybrid system consisting of fuzzy logic (FL), weighted DVM (wSVM), and fast messy genetic algorithms (fmGA). evolutionary fuzzy support vector machine inference model for time series data, EFSIMT). The authors stated that the prediction results obtained with EFSIMT were higher than SVM and comparable to back-propagation neural networks (BPN). Cheng et al. In [16], genetically weighted pyramid operation tree (GWPOT), which is a genetic decision tree consisting of genetic algorithm, weighted operation structure and pyramid decision tree (GWPOT), and HPC pressure performed the endurance estimation. The success of the developed model was compared with ANN, SVM and evolutionary support vector machine inference model (ESIM) and it was stated that better results were obtained.

The most comprehensive study on concrete strength estimation in the literature is Chou et al. It is the work of [17]. Authors 5 different machine learning methods; ANN, SVM, multiple regression analysis and 2 different combined learning models (multiple additive regression trees (MART) and bagging regression trees (BRT)) were applied in the estimation of compressive strength of HPCs and the obtained compared the predicted results. As a result of the study, the superiority of the predictive success of the combined learning models was emphasized. In recent years, most of the studies on estimation with SVM have reported superiority of SVMs over ANNs[18, 19].

The desire to reduce the total load on the structure by reducing the densities of traditional concretes has led to the emergence of more functional, durable and economical structures in recent years. Lightweight concrete is used to reduce the dead load on the building element, thus reducing the dimensions of the load-bearing elements and providing an economic gain. Many studies have been carried out to date to obtain lightweight concrete by using natural or artificial lightweight aggregates in concrete mix. In the studies carried out, the characteristics of lightweight concretes obtained by completely or partially replacing the normal weight aggregates in the conventional concrete mixture with lightweight aggregates were determined. Lightweight aggregates are divided into natural and artificial. The main feature that makes the specific gravity of the lightweight aggregate low is the high void ratio in its internal structures. Today, many artificial or natural lightweight aggregates are used in concrete. Expanded clay and shale aggregates are widely used in the production of lightweight concrete. Today, great developments have been made in computer technologies and all branches of science have started to benefit from these developments. Artificial intelligence methods also have an important place in these developments. In this study, the usability of fuzzy logic modeling, one of the artificial intelligence methods, as an alternative method in concrete technology was investigated. Experimental data of lightweight concrete produced with expanded clay aggregate using regression analysis and fuzzy logic method, which is one of the known estimation methods, were used and comparatively examined [20].

In linear and non-linear analyzes of reinforced concrete structures, basic parameters such as concrete compressive strength, stress-strain behavior, modulus of elasticity, Poisson's ratio obtained from uniaxial concrete pressure tests are taken into account for the concrete material. If these parameters represent the real values in the calculations, it is usual to obtain results that are closer to the truth in the light of the assumptions made in the calculations [21,22]. However, depending on the importance of the structure and its elements, it is necessary to use parameters and models that describe the non-linear behavior of concrete under stresses in order to perform much more sensitive and much more accurate analysis. With the development of technology, the triaxial behavior of concrete can be obtained experimentally and can now be easily used in calculations. Although concrete compressive strength is an important mechanical property that is used especially in the investigation of fracture mechanisms of concrete, a single concrete compressive behavior cannot be recommended for a concrete class or type due to uncertainties in the concrete material. For this reason, many mathematical models have been proposed to represent the triaxial compressive behavior of concrete for different concrete classifications in scientific studies. Each of these models, numbering up to 25, has been developed for different value ranges of characteristic concrete strength and lateral pressure parameters. Even if the behavior of the building materials used in the calculations and designs of the building and building elements is taken into account with the real behavior, this situation is not sufficient for the reliability of the building and building elements. The reason for this is the loads used in building calculations and designs, material strength and behavior, dimensions of building and structural elements, and acceptance of methods used in calculations and designs, etc. are uncertainties. The existence of these uncertainties has led the researches for structure reliability to focus on probability and statistics-based research and calculation methods [23].

1.1 PROBLEM STATEMENT

The concrete compressive strength is playing critical role in producing HPC. The concrete compressive strength estimating in classical techniques need high processing time and also very expertise personals. In previous studies several classical machine learning techniques applied to estimate the concrete compressive strength. The classical techniques such as SVM and ANN are not effective in nonlinear complex datasets. The concrete compressive strength is a highly nonlinear function of age and ingredients. The previous studies applied ANN and SVM directly which lead to the performance of these techniques remain minor. Then, applying feature selection techniques lead to increase the performance of the regression by removing effected features.

1.2 RESEARCH QUESTIONS

In this study, several questions presented in to estimate the concrete compressive strength which is very important factor in producing HPC.

i. What is the HPC ?
ii. What is the concrete compressive strength?
iii. What is the machine learning techniques that can applied to concrete compressive strength estimation?

1.3 THESIS STRUCTURE

The letter includes five chapters prepared as follows:

i. Chapter I: Introduction: concrete compressive strength, problem statement, thesis goal and finally thesis structure.

ii. Chapter II : This chapter provides an overview of the work related to the concrete compressive strength.
iii. Chapter III: Literature review which several previous studies presented and explained in detail form.
iv. Chapter IV: This chapter outlines the research methodology used in this thesis. Optimization algorithms, PSO, GA, ACO, RNN, and the proposed method.
v. Chapter V: Details of the implementation of the experiment and the results obtained for all proposed scenarios and comparison of results.
vi. Chapter VI: Conclusion and Future Work.

2. RELATED WORKS

2.1 HISTORY OF READY CONCRETE

Concrete has an important place in the development of human history and in the works of ancient civilizations that have survived to the present day. B.C. Calcium-based binders have been used by human beings since 3000. Lime-based binders were used in the construction of the pyramids, structures such as the Pantheon and Colleseum were made with pozzolans with natural hydraulic binder properties, and the use of a binder called Khorasan Mortar in Central Asia and Anatolia shows that the history of materials that can be described as CONCRETE dates back to ancient times. Although modern Portland cement was first produced in 1824, the first reinforced concrete structure was built only in 1857. Contemporary concrete chronology is thought to have started in the early 1800s when Louis Vicat produced the first artificial cement and Joseph Aspdin patented Portland Cement. With the discovery of reinforced concrete building systems, concrete has started to be used widely. In the early 1900s, the first "ready-mixed concrete" patent was obtained. With the developments in concrete production technology, the raw materials used and especially the developments in chemical additives, concrete, which has a very wide usage area, has become the most consumed material in the world after water. [24] Ready-mixed concrete, on the other hand, appeared for the first time in Germany in 1903 and then started to be used in the USA within a few years. With the development of a truck mixer vehicle for concrete transport by a Turkish immigrant named Stephanian in 1914, the prevalence of the ready mixed concrete industry in America increased, and many ready mixed concrete companies were established especially after the war years. Especially with the second half of the 20th century, urbanization and infrastructure works accelerated, and ready-mixed concrete and concrete products were produced and spread more.

2.1.1 Aggregate

Concrete aggregate, non-organic, natural or artificial material, which is combined with the binding material consisting of a mixture of cement and water in concrete or mortar construction, generally does not exceed 100 mm (even in construction concrete, it is often formed by unbroken or broken grains not exceeding 63 mm). Some examples of various aggregates used in concrete construction are: sand, gravel, crushed stone, blast furnace slag, baked clay, pumice, expanded perlite and fly ash aggregate obtained from fly ash Aggregates make up approximately 70-75% of the volume of concrete. [25]

2.1.2 Cement

It is mainly defined as a hydraulic binder material obtained by grinding a mixture of natural limestone stones and clay after heating at high temperature. The mesh size of the cement grains is between 5 and 90 microns. Like other binders, cements are composed of alkaline elements such as CaO, MgO and hydraulic elements such as SiO2, Al2O3 and Fe2O3. It is called hydraulic binder because cement gains its binding duty after reacting with water. The proportions of alkaline and hydraulic elements determine the quality of the binder. After a while, the cement becomes a plastic paste after being mixed with water and gradually solidifies in the air or in the water. This solidification phenomenon is called frying. Under normal conditions (28 degrees temperature and in rainless weather), this solidification process starts in the first ten minutes and it is called False Cooking. If it is around an hour, freezing and strength increase. However, this event may vary depending on the conditions, if no chemical setting retarder is used and the air temperature is not very low, freezing will occur in a period of about 10 hours [26].

2.3 MATERIAL

The materials to be used in the correct application of the concrete mix ratios designed for concrete trials must be stable and of high quality. For this purpose, its mineralogical structure is dolomite limestone, its grain density is 2.70 g/cm3 and above, and its water absorption is low (1.2% for crushed sand, 0.5% for aggregate no. 1, around 0.3% for aggregate no. 2).), aggregate, cement, super and hyper plasticizer additives, whose particle distribution complies with TS EN 933-1 standard, were used. The importance of quality aggregate is that it has a high specific gravity, low water absorption and a void-free structure. Natural sand (yellow sand) is used to reduce the need for water. Natural sand is round in structure and requires less water than angular crushed sand [27].

2.4 CONTENT AND MIXTURE OF CONCRETE

After the cement, which is a hydraulic binder, is mixed with water, the paste formed solidifies over time. With this event occurring inside the concrete, the concrete hardens and gains strength.

One of the most sought-after properties of hardened concrete is its high strength and firmness. The leading condition for this is to keep the void in the concrete at the lowest level. Concrete with high strength and stiffness can be obtained to the extent that the spaces between large-grained aggregates are filled with smaller-grained aggregates and cement paste. Strength, firmness and workability of concrete; Besides the amount of cement and water in the mixture, the mixing ratio of the aggregate is also effective. The amount of cement must provide a minimum value in order to obtain the required compressive strength and to protect the reinforcement to be placed against corrosion. The amount of cement in 1 m3 of poured and compacted concrete is called dosage. Depending on the properties of the mixture and the concrete obtained, this value varies between 240-380 kg/m3. It is wrong to assume that only the amount of cement is important in the strength of concrete. It should not be forgotten that the arrangement of aggregate granulometry, water/cement ratio and placement are also important. In determining the concrete composition, it is the most correct way to comply with the sieve mixture curves given in TS 706, to comply with the mixture determination principles given in TS 802, and to evaluate the test results by taking samples from the prepared concrete. However, the ratios (water/cement)/sand/gravel=(0.55/1.00)/3.0/4.5 can be taken as a starting value, based on the weight measure [28].

The prepared concrete is poured into the molds, which are arranged according to the shapes of the building elements and contain steel reinforcement bars. Detailed information on the preparation, transportation, placement and maintenance of concrete until it hardens is given in TS 1247 and TS 1248. It is important for the molds to be clean and wetted, and to have a flat surface in terms of the ease of demoulding and the appearance of the concrete surface obtained. The simple test that can be done to determine the suitability of the consistency of the concrete during placement is the slump test. The concrete prepared in this experiment is filled into a truncated cone with a height of 300mm, top and bottom diameters of 100mm and 200mm and no bottom. For each triplicate filling, 25 blows are applied to the bottom of the cone with a 12 mm diameter and 600 m long stick. 3 minutes after the end of the filling, the cone is removed and the slump of the concrete is measured. In normal construction elements, this collapse should be between 20-100mm. Small slump generally corresponds to low water/cement ratio and high concrete strength. Large slump generally corresponds to high water/cement ratio and low concrete strength. However, the small slump reduces the workability of the concrete and makes placement difficult. This causes the strength of concrete to decrease. After placing the concrete in the mold, care should be taken to compact it with a vibrator. In this way, voids are prevented from remaining in the concrete, and the two materials work together by wrapping the concrete around the reinforcement [29].

Today, the application of ready-mixed concrete is becoming widespread. The concrete prepared in the concrete production facility is brought by truck mixers and poured into the mold with pumps. The important thing at the construction site is to pour the concrete into the mold and place it before it hardens. Since the fresh concrete cannot support itself, the formwork and the scaffolding carrying it must be of a type that can carry the weight of the concrete and they must be dismantled after the concrete hardens and reaches a certain strength. Since concreting continues in ordinary buildings, layer by layer, the scaffolding of the part to be concreted is usually supported on the lower floor. The fact that the concrete in this section is not sufficiently hardened and the fresh concrete on the upper floor is heavy may cause significant stresses on the building elements in some cases. Extending the mold removal time can be considered as a solution [30].

Concrete hardens by using the water it contains in hydration over time, and the water required for the chemical reaction is lost by evaporation before the chemical reaction ends, causing the concrete to not gain the necessary strength. For this reason, it is important to care for the concrete after it is poured into the mold. Protecting the concrete from extreme weather conditions, such as very low or high temperatures, excessive wind, after the casting is completed, ensures that the hardening takes place regularly. It may be recommended to cover the concrete with wet sacks to keep it moist. Since curing slows down at low temperature, the mold removal time needs to be extended. Under normal conditions, concrete reaches 70% of its strength in 28 days. When the concrete cannot be poured continuously and is interrupted, the work joint is formed. It is appropriate to bring the work joint to the least stressed areas of the building elements and to clean and roughen these joints before the start of concrete [31].

Concrete mixing ratios have reached certain standards as a result of both experience and academic studies and researches in the field of engineering. There are standard concrete mixing ratios such as C10, C20, C30, C35 in the market today. While the expressions starting with C here express the standard class of concrete, the numbers on the right show the ratios of cement, sand and aggregate in the concrete, respectively. For example, if the cement ratio is 1 in C15 class concrete, the sand and aggregate ratios are 2 and 4, respectively. The amount of remaining water generally differs between applications. As the aggregate ratio in the concrete increases, the compressive strength of the concrete will increase. Sand, on the other hand, gives workability to concrete. These rates should be determined correctly according to the nature of the application. The water ratio is one of the most important issues for concrete. Too little or too much water can reduce the strength of the concrete or make it difficult to work [32].

2.4 DURABILITY IN CONCRETE

Concrete durability is its resistance to aggressive elements in the external environment. In addition to these elements, it is possible for the components that make up the concrete to react in some cases. Like the Alkali-Aggregate reaction. Such internal corrosion events can be exacerbated depending on the external environment [33].

Concrete should be resistant to natural chemical damages and should not lose its qualities as a result of physicochemical external factors. For this, it is required to have sufficient chemical resistance (durability). As a result of the reaction of any element made with cement with cement, its strength should not increase but decrease over time.

2.5 CONCRETE PETROGRAPHY

Since concrete is an artificial stone, its microstructure can be examined. Petrography in hardened concrete is simpler but more complex than conventional petrography. It is simple because all minerals do not have to be examined and counted, and observations made in petrography are complex because they have to be made into a composition in a cause and effect relationship. While examining the samples prepared with special techniques, important conclusions can be reached about the quality of the concrete by evaluating the clues about the aggregate distribution, crack development, cold joint formation, the void structure of the repaired concrete, the distribution of the binder and the water-cement ratio [34].

Concrete petrography is a technique that is generally applied to remove question marks from the heads. For example, if the material did not pass the strength test, if a serious defect was observed, if there were uncertainties about the amount of air, if a work out of the standard was done in practice, if concrete was poured under the rain or if serious cracks occurred when the concrete was young.

Today, when it comes to petrographic examination, the most mentioned technique is the fluorescent epoxy technique. The petrographic examination can be divided into four parts. The first is visual and hand inspection, samples cut from the field or cured in the laboratory are inspected visually and manually before they are cut and analyzed for petrographic analysis. Significant defects, cracks, reinforcement, voids or gel formation on the sample are photographed and recorded. After visual inspection, the concrete sample is cut to obtain three different preliminary samples, from which one sample for plane section analysis, one sample for thin section analysis and one sample for air void analysis are prepared.

Concrete petrography is an important technique especially in the resolution of judicial cases. It has a system that is learned over time and is difficult to implement. The sample preparation phase is also vital in the analysis, it can be said that it is "an art in itself". However, after all these difficulties have been overcome, the data obtained through petrography provides the necessary information about concrete. It plays a guiding role in producing a high-tech concrete. Thus, the homogeneity of the mixture, the distribution of aggregates, the effectiveness of mineral additives can be adjusted, and the harmful effects that may come from outside can be minimized.

Besides the water content, it also largely determines the strength and workability of concrete. As the amount of water increases, the workability (more fluid) of the concrete will be. However, it reduces the strength of concrete. If you keep the water too low, the workability of the water will also decrease. Therefore, it will be difficult to place such concrete in the structure. The amount of water required can vary for the same concrete volume for various concrete classes. Therefore, a balance must be found during concrete mixing at the construction site.

2.6 CONCRETE COMPRESSIVE STRENGTH

Concrete is a composite building material that is generally used in the production of bearing elements in buildings. The most obvious criterion of the bearing capacity of concrete is its compressive strength. Concrete compressive strength is the most easily determined property among the properties of hardened concrete. It also gives the most accurate information about compressive strength and concrete quality. Concrete strength; It is the greatest resistance that concrete can show against deformation and breakage caused by the loads on it. It has been observed that concrete properties improve over time, just like in living systems. Since concrete is a composite material, it does not have the properties that its components show separately when combined. An important part of the behavior of concrete emerges as a result of the interactions between these components. In various studies on concrete, the relationships between some properties of the material and compressive strength have been investigated and it has been observed that various properties of concrete change in the same direction as compressive strength. Because of this relationship, the compressive strength of concrete is accepted as the quality criterion of concrete. However, the relationship between other properties and compressive strength is not certain. In special applications, it is necessary to examine the feature that is important in the application in question experimentally [35].

3. LITERATURE REVIEW

There is a lot of work involved in the conventional and detailed estimation of the literature practice. Studies show that ANN has more successful results than comparisons.

In [36] Kadir Güçlüer et al. compressive strength data for hardened concrete samples were used for 7 and 28 days, and the compressive strength of concrete was compared with artificial neural networks (ANN), decision tree algorithms (DT), vector machine support (SVM) and linear regression (LR). . The objective of the study was to determine the algorithm with the most successful performance. The study used the specific gravity, water content, Schmidt hammer, ultrasonic pulse frequency, and relative humidity of the hardened concrete as the input, and the compressive strength of the concrete was determined as the output variable. In the analyzes, the best correlation coefficient (R2) was 0.86 and the best mean absolute error was 2.59 using the DT algorithm. Data for the most successful analyzes were obtained from cement samples cured for 28 days. As a result, the DT algorithm was found to have the fewest errors and is therefore the most suitable for evaluating the compressive strength of concrete.

In [37] M.A. DeRousseau et al. evaluates the effectiveness of machine learning (ML) methods to predict the compressive strength of concrete in the field. We use field and laboratory data to train and test increasingly complex machine learning models to determine the most efficient model for a given domain. -The concrete is being laid. The ability of ML models trained on laboratory data to predict the compressive strength of concrete in the field is assessed and compared to models trained on field data only. The results confirm that a Random Forest ML model trained with field data shows the best performance in predicting the compressive strength of concrete in the field; The RMSE, MAE and R2 values were 730 psi, 530 psi and 0.51, respectively. We also show that hybridizing field and laboratory data to train machine learning models is a promising way to reduce common overestimation problems that occur with laboratory-trained models that are used in isolation to predict resistance to resistance. Compression of concrete placed on the ground.

In [38] Khoa Tan Nguyen et al. proposes two different machine learning approaches for predicting the compressive strength of fly ash geopolymer concrete. Experimental work was carried out with 335 mixing ratios to obtain data for training and validation processes. In the proposed models, fly ash, water glass solution, caustic soda, coarse aggregate, fine aggregate, water, sodium hydroxide concentration, cure time, and cure temperature were accounted for as nine input variables, while compressive strength compressed the output. function. The performance of machine learning approaches was assessed using a set of three metrics, including correlation coefficient (R), mean absolute error (MAE), and root mean square error (RMSE). A good correlation was obtained between machine learning models and experimental results. The proposed models can be used to create a standard mix and calculate the proportions of geopolymer fly ash concrete mix.

In [39] Debaditya Chakraborty et al. Improve predictability and explain the capabilities of our machine learning model using pipeline, automatic feature selection, cross-validated hyperparameter optimization, and a game theory approach to generating explainable information that could lead to the development of materials with new or vastly improved properties.

In [40] Omar R. Abuodeh attempts to resolve this ambiguity using two deep machine learning techniques: sequential feature selection (SFS) and neural diagram interpretation (NID) to identify critical hardware components that affect the ANN. 110 UHPC compressive strength tests with varying amounts of material were collected in the database to form the ANN. As a result, four hardware components were selected; mainly cement, fly ash, silica dust and water. These hardware components were then used in the ANN to compute more accurate predictions ($r2$ = 80.1% and NMSE = 0.012) than in the model with eight hardware components ($r2$ = 21.5% and NMSE = 0.035). Finally, a nonlinear regression model was developed based on four selected hardware components and a parametric study was performed. It was concluded that using KNN with SFS and NID significantly improves model accuracy and provides valuable information on KNN compressive strength predictions for various BUHP joints.

In [41] Benjamin A. Young et al. presents the first analysis of a large data set (> 10,000 observations) of measured compressive strengths of actual (in situ) mixtures and corresponding actual mixture ratios. Predictive models are used to examine the relationship between the mix design variables and strength, and then provide an estimate of strength (28 days). These models are also used in the laboratory. Based on the force measurement data set by Yeh et al. (1998) and compares the performance of the model for the two data sets. To illustrate the value of these models, in addition to simply predicting strength, they are used to design optimal concrete mixes that minimize cost and carbon footprint while meeting established strength goals.

In [42] Umur Korkut Sevim et al. proposed a new predictive model for predicting the compressive strength of mortar samples with different properties. For this purpose, 8 different fly ash was used in the mortar mixture to replace the weight of the cement. Various fly ash solutions were made with additions of 10%, 20%, 30% and 40% fly ash. The compressive strength of the mortar samples made after 1, 3, 7, 28, 90 and 365 days was evaluated. A total of 196 prototypes were manufactured and mechanically tested. The relationship between compressive strength values (dependent value) and $SiO_2 + Al_2O_3 + Fe_2O_3$ content, age and fly ash replacement factors (independent values) was determined by machine learning methods such as artificial neural networks (ANNs) and network adaptive networks. ... Blurry output. predictive systems (ANFIS). The results were compared with the traditional statistical multilinear regression (MLR) method to validate the proposed models. Based on test results, keep in mind that Anfis HA based model provides better results for evaluating compressive strength based on fly chemistry, e.g. $SiO_2 + Al_2O_3 + Fe_2O_3$, the proportion of fly ash in ash ripples, has an incentive effect for future of research Sample solution and age.

In [43] Mosbeh R. Kaloop et al. examines the SPline Multivariate Adaptive Regression (MARS) model as a feature extraction technique to extract the optimal inputs used for HPC design. In addition, the extracted function is passed on to a Gradient Tree Boosting Machine (GBM) learning technique for CCS prediction. In addition, a comparative study with different structural models (peak nuclear regression and Gaussian process regression) was carried out to determine the reliability. A total of 1030 data sets with eight input variables, i.e. cement, blast furnace slag, water, plasticizer, fine grain, age of the concrete, etc. are used as inputs for the estimation of the CSC HPC. The results of the analysis show the relative importance of the weights of each parameter during GBM treatment. Among the six most important parameters, specific age proved to be very sensitive for predicting squamous cell carcinoma. In addition, the integrated MARS-GBM approach shows a simplified approach to HPC-CCS prediction based on various fitness metrics (e.g. the correlation coefficient and mean absolute error are 0.965 and 0.037 MPa, respectively). Hence, this study concludes that such a holistic approach can be a viable option to achieve higher performance with statistical responsibility.

Şamandar (2015) estimated the compressive strength of normal weight concretes containing fly ash with ANN in his study named Estimation of the Compressive Strength of Normal Weight Concretes Containing Fly Ash Using Artificial Neural Networks Method. In the training, 103 experimental data were used and cement content, water content, fly ash amount and slump values were determined as inputs. In the study, different network structures were studied and their correlations were examined. It was stated that the network structure consisting of a hidden layer and 7 neurons gave the best results. The results showed that artificial neural networks have potential to predict the compressive strength of concretes containing fly ashv[44].

Öz Bakır and Nasuf (2015) stated that it is possible to determine the effect of physical and mechanical properties of aggregate on strength properties of concrete only through experiments. It was stated that different methods were used because the experiments took a long time and were often not economical. The physical properties of the aggregates obtained from 14 different quarries were determined by experiments in the study. Concrete samples were prepared and the 7th and 28th day strengths of these concrete samples were measured. By keeping the concrete components other than the aggregate constant, the compressive strength of the concrete was monitored in the changing aggregates. In the study, models were developed using ANN and the results of the concrete compressive strength values estimation obtained by the experiments were compared [45].

Tsamatsoulis (2015) used two commonly used techniques (multiple linear regression and ANN) to estimate the 28-day compressive strength of Portland cement. Three-layer ANN network with one or two nodes in the hidden layer and eight different models including a cascade ANN are compared using sigmoid, hyperbolic, tangent and radial functions. As a result, it has been reported that the equations should be updated in the estimation of concrete compressive strength with the emergence of new results every day in the application of the dynamic model [46].

Niko et al. (2015) used Evolutionary ANN as a combination of evolutionary search procedures such as ANN and Genetic Algorithm. Data of cylindrical concrete samples with 173 different properties were used in the creation of the models. Water-cement ratio, maximum sand dimensions, amount of gravel, cement, 3/4 sand, 3/8 sand and soft sand parameters were used as inputs. In addition, the number of layers, nodes and weights of the ANN models were optimized using GA. To evaluate their accuracy, the optimized ANN model and the multiple linear regression model were compared. The results confirm that the proposed ANN model has more flexibility and accuracy in predicting the compressive strength of concrete [48].

Khademi and Behfamia (2016) evaluated the capacity of concrete to predict compressive strength on the 28th day. Considering the specific concrete properties as the input variables, ANN was constructed and the compressive strength of the concrete was estimated. An ANN model with 8 inputs and 15 hidden layers was used in the test of 150 different samples prepared for cement strength measurement on the 28th day. Training, testing and validation values confirm that ANN is a suitable model for estimating the compressive strength of concrete on the 28th day [49].

Chopra P et al. (2018), an ANN model was proposed for the 28th, 56th and 91st day strengths of concrete and compared the ANN model with data mining machine learning techniques Decision Tree and Random Forest methods based on R2 and RMSE values. It has been determined that ANN gives better results in estimation of strength and these results are very close to the real value with the result of R2 = 0.956 at 91 days strength compared to the real values [50].

4. MATERIAL AND METHODS

4.1 OPTIMIZATION ALGOROTHMS

Optimization is the process of obtaining the most suitable solution by providing certain constraints for the given purpose or purposes [51]. Algorithms developed in linear programming models have a continuous decision variable and can reach the solution quickly. It should be noted here that the best point of the problem is already at one of the intersection points and since the solution only deals with these points, a solution can be reached quickly. However, in problems that we describe as real world problems, we may not be able to reach the result so easily. In order to solve real-world problems, we must first have an objective function. This objective function does not always have to be a linear function, either. In our objective functions, our decision variables can be integers. Since we are talking about randomness, we work in space, the point we are at between a variable and our objective function will give an answer for negative or positivity.

In order to find the best solution for the structure we have established to solve the problem in the algorithm, methods in which all variables are tried one by one are preferred. However, even if we solve this process on the computer, we need to make the job of finding the best result professional by trial and error, since we will not have done a best practice job. We use intelligent search algorithms to optimize the time and run the trial.

While using intelligent search algorithms, we can also make logical modifications that are suitable for our problem. Just like in the logic of operating systems to take and evaluate the operations piece by piece, intelligent search algorithms aim to reach the result quickly by searching in smaller areas in order to solve the problem. In the piecewise search process, it considers the problem as small pieces and if it has reached the best solution in the piece it is working on, it keeps it as a node and moves to the other piece, continuing the process like this, and comparing the nodes among themselves and finding the best one. Thus, it is fast as it does not look at all nodes at once and will stop working on the first node it finds the result.

Although we seem to reach the result with traditional intelligent search algorithms without the need for heuristic algorithms, the weakness of these operations is due to the concern that the number of nodes is high and the operations here can be troublesome. In other words, in such a case, these intelligent search algorithms would not have returned the result at the optimum speed we wanted.

Exactly in such a scenario, we can turn our problem into a real-world problem and run it on heuristic algorithms instead of traditional intelligent search algorithms, and get more optimal results. The aim of this article is to examine metaheuristic algorithms such as GA, ABC, PSO in the literature, and to determine the weaknesses of these algorithms, what changes can be made, what additions and mechanism changes have been made in the literature. In this section we will presented several common used optimization algorithms.

4.1.1 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based optimization technique developed by Kennedy and Eberhart in 1995, inspired by the two-dimensional behavior of bird and fish flocks [52]. These two-dimensional behaviors; It requires a 'knowledge-sharing' approach, such as being able to adapt to their environment, find rich food sources, and escape from predators. Thanks to information sharing, swarms follow the swarm element closest to the target while foraging for food or escaping from the predator and update their speed and position according to the most successful member. In order to find an optimum or near-optimal solution, PSO first creates particles, each of which is a solution candidate. These individuals are randomly selected within certain limits. The population realized for the solution is formed by the gathering of individuals. When the particle moves, it sends its coordinates to a function and the particle's fitness value (distance from the optimum solution) is measured. The particle's position information (coordinates), speed (how fast it moves in the solution space) and the current best fitness value and the coordinates it obtained this value should be kept in memory. How its velocity and direction will change in each dimension in the solution space will be a combination of its neighbors' best coordinates and its own personal best coordinates.

PSO has been used successfully in a wide variety of application areas in the literature. A PSO-based image segmentation approach is presented in [53]. Using a mixture of Gaussian probability functions, the histogram of an image is fitted and the PSO algorithm calculates the parameters of this mixture of probability functions. Thus, the error between the density function and the actual histogram is minimized. In [54], PSO has been applied to some mechanical design problems with limitations. In these problems, besides the function to be minimized, there are other equation sets that limit the parameters of the functions. The solution of these rather complex problems with PSO was compared with other methods and it was determined that PSO was the most advantageous and successful method. In [55], PSO was applied to the reactive power and voltage control (VAR/VAR control) problem, which was defined as a nonlinear optimization problem in power systems. The situation to be minimized here is the total power loss in the target power system, provided that voltage stability is also ensured. In [56], PSO was used for FPGA deployment and routing. The algorithm has ensured that the link lengths between the configurable logic blocks (CLB) are minimized. In [57], PSO is used in the optimization of fuzzy logic controller designed for off-grid photovoltaic system. The PSO has optimized the membership function and rule set used in the controller's design. In another study, PSO was applied to the circuit decomposition problem and the parameters of the decomposition approach were determined by PSO [58]. Here, the PSO-based approach optimized the number of test vectors, the number of parsing, and the critical line. In [59], the PSO communicates with a swarm of moving sensors or robots; It has been used for maximum application of local and global tasks such as fire suppression, mine detection and radioactivity determination. In [60], a hybrid structure was created using PSO and evolutionary algorithm and this structure was used in the evolution of combinatorial logic circuits. The aim of this study is to perform 100% functional combinatorial logic circuit evolution with the minimum number of gates. At the end of the study, it is stated that the hybrid structure successfully achieves this aim.

4.1.2 Ant Cony Optimization

ACO was developed based on the behavior of real ant colonies. One of the most basic elements of the technique is the pheromone chemical, which is used as a communication tool and shows the quality of the solution in problems [61]. A pheromone is a chemical secreted from their bodies that real ants use as a means of communication and direction finding. The pheromone traces are updated by the ants and represent information. The presence of a pheromone trace on a road indicates the quality of the road and increases the probability of preference. In ACO, artificial ants search for the shortest path on the model made by considering real distances. The pheromone traces on the roads are also artificially updated in proportion to the frequency of the ants.

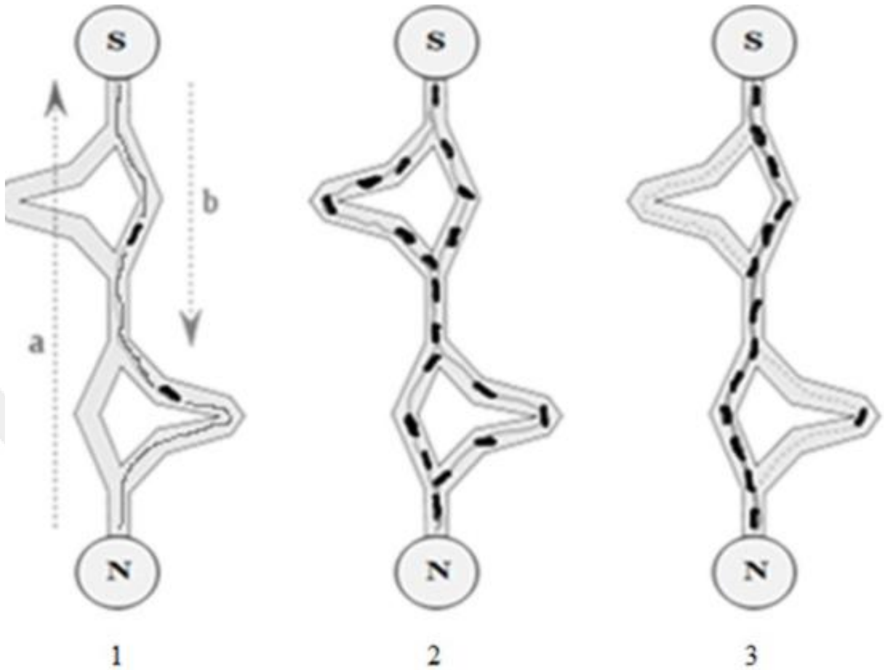

Figure 4.1: ACO Process.

4.1.2 Genetic Algorithm

Genetic Algorithm, used in the field of Artificial Intelligence, is a kind of algorithm that searches for the best spot. It is concerned with seeking a solution to a problem. If we can turn a real-life problem (such as how to place containers on a dry cargo ship, how to get from one point to another, or how to create the most suitable delivery route) into a search problem, we can solve this problem with Genetic Algorithm. The Genetic Algorithm (GA) performs a permutation based optimization and is a function that searches for convergence criteria over probabilities. It is a method of search and optimization that works similarly to the evolutionary process observed in nature. The Genetic Algorithm has been described in the literature as follows: The Genetic Algorithm is a powerful evolutionary strategy inspired by the basic principles of biological evolution. The researcher should first define the variable type and the problem he is dealing with correctly and make the coding according to this definition. Then, the fitness function, which is one of the inputs of the algorithm, is defined and this is the objective function that needs to be optimized. Genetic operators such as Crossing and Mutation are applied stochastically at many stages of the evolutionary process, so their probability of occurrence must be determined. Finally, convergence criteria should be met and the problem should be solved with optimal cost. GA does a global search, not a local one, to solve the problem [62]. If there are too many factors affecting the problem, the use of Genetic Algorithm in the solution is recommended by the literature. Briefly, the working principle of the Genetic Algorithm is as shown in figure 4.2.

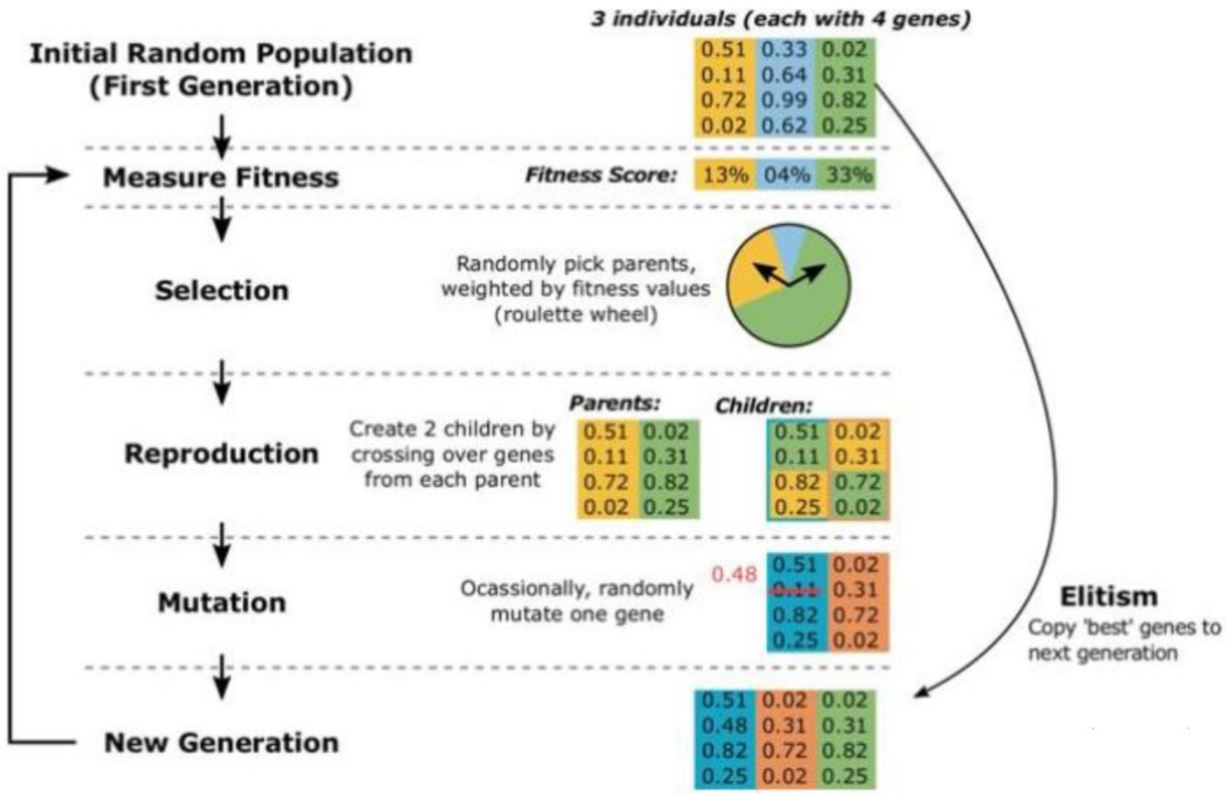

Figure 4.2: GA Process.

The flowchart of the algorithm presented in the figure 4.3.

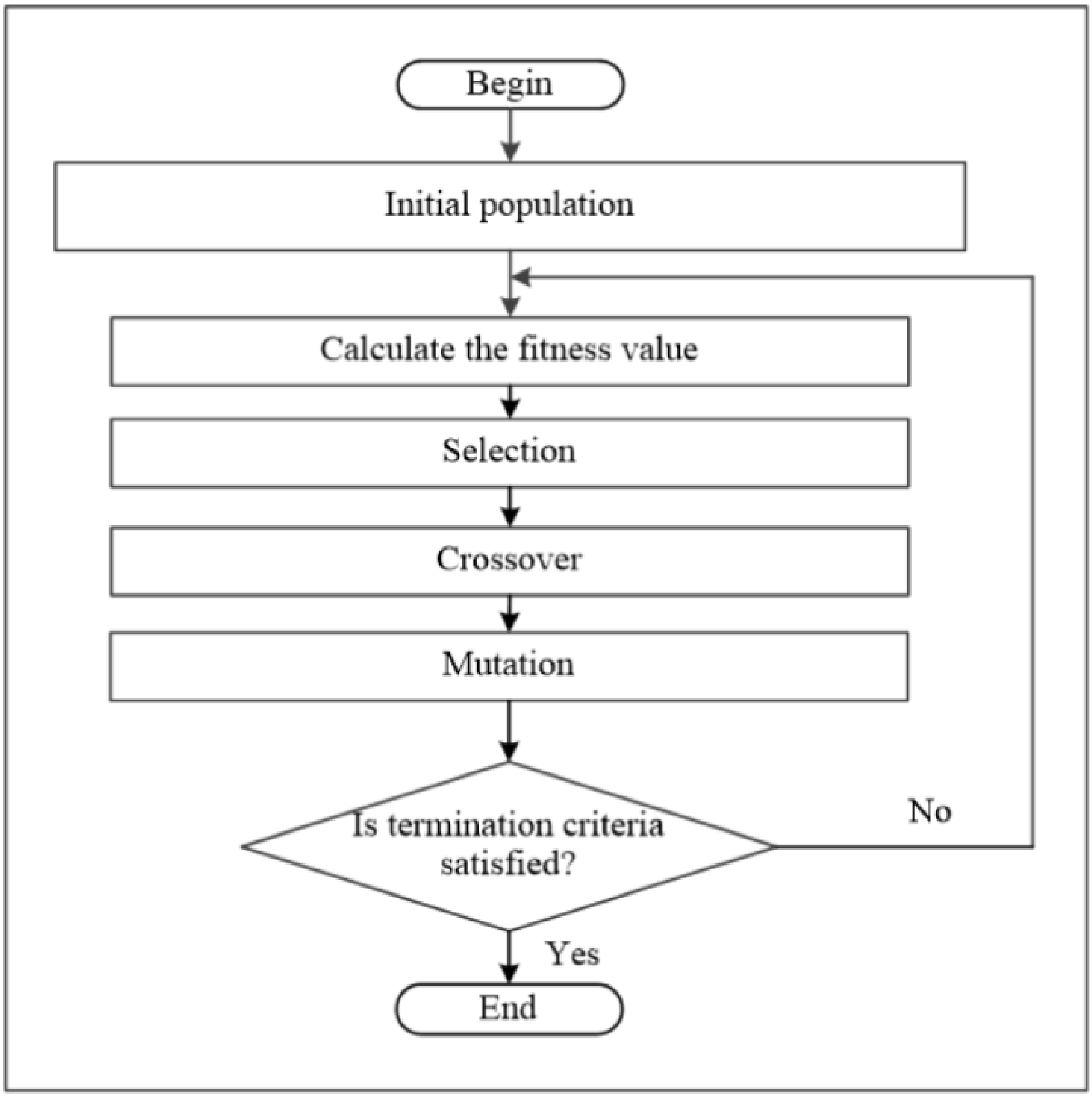

Figure 4.3: GA flowchart.

The representation of the problem in individuals varies from problem to problem. The most important factor in deciding the success of genetic algorithms in solving the problem is the representation of individuals representing the solution of the problem. Each individual in the population has a fitness function that decides whether it will be a solution to the problem. Individuals with a high value relative to the value returned from the fitness function are given the opportunity to multiply with other individuals in the population. These individuals produce new individuals called children at the end of the crossover process. The child has the characteristics of the parents (mother, father) who created him. Since individuals with low fitness values will be less selected when producing new individuals, these individuals are excluded from the population after a while. The new population is formed by the multiplication of individuals with high fitness in the previous population. At the same time, this population contains most of the characteristics of the individuals of the previous population with high fitness. Thus, good traits spread through the population over many generations and are combined with other good traits through genetic processes. The more individuals with a high fitness value come together and create new individuals, the better a working area is obtained in the search space. In order to find the best solution to the problem; The concepts used in the genetic algorithm are used in a similar sense to the theory of evolution in biology. In natural life, populations are formed by the coexistence of individuals. The population created for the GA algorithm is formed by the gathering of many individuals, in other words, by the gathering of many possible solution candidates. Candidate solutions are kept in sequences coded according to the problem. Each element that makes up this array is called an individual, and each individual represents a specific region in the search space.

In the genetic algorithm, the first starting individuals are usually randomly generated, but this is not a requirement. Especially in very constrained optimization problems, better candidates can be created by paying attention to some of the defined constraints to create the starting individuals. As a result of exposing individuals to the fitness function process, the fitness value, which evaluates how close the solution is to the optimal solution, is determined. The genetic algorithm with the initial population created works with three evolution operators. These; selection, crossover and mutation operators. In general, each of these operators is applied to each individual of the population that will form in the next generation.

Selection is the process of selecting parent individuals to create new individuals based on their fitness values in the population. The crossover operator is applied after the selection process and expresses the mutual replacement of certain parts of the chromosomes of the parent individuals and thus the formation of individuals with new characteristics. The mutation process is the process of changing a gene in any of the chromosomes of the newly formed individual depending on the probability of mutation.

There are various methods to terminate the genetic algorithm process. These methods are; When the desired solution is found during the operation of the algorithm, when the total number of iterations defined at the beginning of the GA is reached, or when the fitness value remains constant, the solution represented by the best individual found is presented as the most suitable solution found for the problem.

4.2 MACHINE LEARNING

We can explain the difference between artificial intelligence algorithms that do not include machine learning, which we can call "classical" or "traditional" algorithms, and machine learning algorithms with the following simple example: Imagine a human baby who has no knowledge of animals. This baby will not be able to distinguish between cats and dogs. In this thought experiment, let's imagine the baby as an artificial intelligence algorithm and the person who will teach him the differences as a computer scientist [63].

In classical artificial intelligence applications, instead of teaching the baby the difference between cat and dog, we give him a full set of instructions that will enable him to distinguish between cat and dog. These instructions should be prepared in such a way that this ignorant baby should be able to both follow those directions and distinguish between cat and dog mostly correctly. It is obvious how difficult this is for both the baby and the teacher.

On the other hand, as you may have noticed, we don't really need to do this to increase baby's success: If we give the baby lots of pictures of cats and dogs and repeatedly tell which is which, the baby will at some point begin to distinguish the two with high accuracy. This is exactly how machine learning algorithms work, as the name suggests. Of course, computers unfortunately do not come with a learning algorithm in them when they are built. Computer scientists themselves design and adapt the most suitable machine learning algorithm for each problem. Machine learning is essentially built around this logic. Many artificial intelligence applications that we have seen recently are actually machine learning applications. Machine learning is indispensable in real life for most artificial intelligence applications that we are used to seeing in science fiction movies; Therefore, the concepts of "machine learning" and "artificial intelligence" are getting more confused [64].

At this point, although we have largely avoided the conceptual confusion by revealing the difference between the concepts of machine learning and artificial intelligence, there is one more step we need to take: Although machine learning is a narrower concept than artificial intelligence, it still includes many different algorithms and It is a method field. That's why the concept of "machine learning" still doesn't adequately describe the products of popularization we're talking about. Therefore, now, by talking about deep learning, which is a sub-branch of machine learning, we will both avoid popular broadcast-level conceptual confusion and better understand why artificial intelligence has been so popular for the last 10 years.

4.2 AI IN CONSTRUCTION PROJECTS

The entry of artificial intelligence into the construction industry is inevitable. Especially in the next few years, completely artificial intelligence management will take place in all areas of the construction industry. This has become inevitable in order to keep up with the growth standards and to prevent the construction sector growth rates from going backwards. So what exactly is the future of artificial intelligence in the construction industry? How will progress be made?

4.2.1 Direct Prevention of Cost Overruns

In all major projects, the projected budget is almost always exceeded, although the best crew and equipment are provided. The system that measures the type of contract, the size of the project and the level of competence of the people who manage the project and calculates the projected costs for the project is called the Artificial Neural Networks system. On the other hand, it can be used to make data forecasts with the planned start and end dates of the project and realistic approaches. Artificial intelligence enables the personnel involved in the project to access training materials based on experience so that they can improve their knowledge and skills. This can save time, as it will shorten the time it takes to add new resources to projects. Ensuring time savings means shortening the delivery times of the project [66].

4.2.2 Better Designed Buildings

Building Information Modeling is the system used in this field. This system is a 3D model-based process that can give architects and engineers an idea about planning, constructing and designing the infrastructure of the building more efficiently. In order to design and plan the construction of a building to be built, in the case of the preparation of 3D models, the engineering, architectural, electrical, mechanical and electrical installation systems should be made according to the order of activity, which should be considered by the relevant teams. The main challenge here is to prevent models from different disciplines from conflicting with each other. The best way to achieve this in the industry is to teach and practice the use of machinery. In this case, different software should be used in order to implement different and good designs [67].

4.2.3 Minimizing Risk

Safety, quality, time and cost risks can be found in every construction activity that emerges as a project. As the growth of the project requires different areas to work together, the risk situations will increase even more. In this respect, artificial intelligence is capable of easily detecting all risks to be found in the project. Project teams will ensure that the necessary resources in this respect can be applied to the correctly identified risks. The artificial intelligence to be used here is capable of producing automatic solutions to emerging or emerging problems.

4.2.4 Planning Phase of the Project

By 2018, a system was developed and put into operation that could predict the necessary budgets while the projects were being carried out. The company, which puts the application into effect, carries out data transfer processes by using robots in the construction industry, and accordingly, it can evaluate and measure the progress of its different subprojects. This method, which is implemented with the application of artificial intelligence, proceeds completely automatically. Problems that may arise have the opportunity to be solved by transferring them in small sizes. In the coming years, artificial intelligence algorithms, defined as 'Reinforced Learning', are expected to be implemented. In this way, endless combinations and alternatives can be evaluated in the same and similar projects. It will create a chance to offer the better where it can optimize the best way in project planning and have the opportunity to correct itself [68].

4.2.5 Making Construction Sites Productive

When we think of today's technology, all of the human activities such as laying bricks, welding, demolition, pouring concrete can easily be done with construction machines designed with artificial intelligence. Similarly, bulldozers, whose programmer is human, can perform excavation operations. These methods, which are used in construction sites, not only shorten the time required for the completion of the project, but also offer people much more time. The people who manage the project have the chance to monitor the works being carried out in the construction area in real terms with cameras, face recognition systems and similar technological opportunities. It can be easily learned whether the productivity of the employee complies with the established procedures.

4.2.6 Construction Safety

Occupational accidents and worker deaths in the construction sector are exactly 5 times higher than in other sectors. The main causes of these deaths in the construction area are; It can be defined as falling from a height, getting stuck in any object, electric shocks, being stuck between objects. An important US-based company is developing an application with artificial intelligence to minimize these deaths. Thanks to this artificial intelligence system, it is aimed to provide methods such as the evaluation of risk factors in the construction site and the warning of workers who do not take safety precautions. The company states that it has the opportunity to fully rank the risks, and that immediate action can be taken in case of high risks.

4.2.7 Relieving Labor Shortage

The shortage of labor force and low productivity in the industry have led construction companies to quickly turn to artificial intelligence systems. According to the researches, by controlling the data and making the analysis, the construction companies have the potential to provide an efficiency of 50%. At the end of this research, construction companies have started to turn to artificial intelligence systems in order to make plans to increase the productivity between machines and workers, how much the total work in the project phase is. The artificial intelligence system in question; It has the capacity to evaluate the stages of the progress of the project, the positions of equipment and workers, and analyze which areas are sufficient and in which areas they are lacking.

4.2.8 Construction Outside the Site

Construction companies continue to use building materials produced by robots in factories at an increasing rate. In this way, all the mechanisms required for construction are produced by the factories, leaving the details for the workers working on the construction site to complete.

4.2.9 Use of Artificial Intelligence After Construction

After a building is completed, the use of artificial intelligence does not end, it continues. In particular, the modeling of the building and information about its structure can be stored. Artificial intelligence systems can take the necessary measures to solve the problems in this respect.

4.3 PREDICATION USING REGRESSION

For example, an agricultural engineer might want to know the relationship between wheat yield and the amount of fertilizer, an engineer might want to know the relationship between pressure and temperature, an economist might want to know the relationship between income level and consumption expenditures, an educator might want to know the relationship between students' absenteeism and success rates. Regression not only shows the functional form of the linear relationship between two (or more) variables, one dependent and the other as an independent variable, as a line equation, but also provides an estimation about the other when the value of one of the variables is known. Usually these two (or many) variables all have to be on a quantitative scale [69].

In regression, one of the variables must be the dependent variable and the other must be the independent variable. The logic here is that the variable on the left in the equation depends on the variables on the right. The variables on the right are independent of other variables. The lack of interest here means that these variables will have an impact when we put them in a linear mathematical equation. Multicollinearity and cascading dependency problems are not implied.

4.3.1 Recurrent Neural Network (RNN)

Strict feedforward structural enterprise fixes not uphold a short-term reminiscence. Any reminiscence belongings are owing to the method historical inputs are re-presented to the network. A humble RNN has activation feedback which exemplifies short-term memory. A national layer is efficient not lone with the outside input of the network but also with activation after the earlier forward propagation. The feedback is adapted by a group of weights as to allow involuntary version finished learning (e.g. backpropagation) [70].

For humble structure and deterministic activation functions, learning can be attained applying alike gradient descent events to those foremost to the back-propagation technique for feed-forward networks. When the activations are stochastic, pretend hardening methods may be additional suitable. The next will appearance at a insufficient of the greatest significant kinds and features of RNN. Recurrent neural networks (RNN) are a class of artificial neural networks in which the connections between nodes form a directed loop. This allows it to exhibit dynamic temporal behavior. Unlike feedforward neural networks, RNNs can use their input memory to process arbitrary sequences of inputs. A typical RNN shown in figure 4.4:

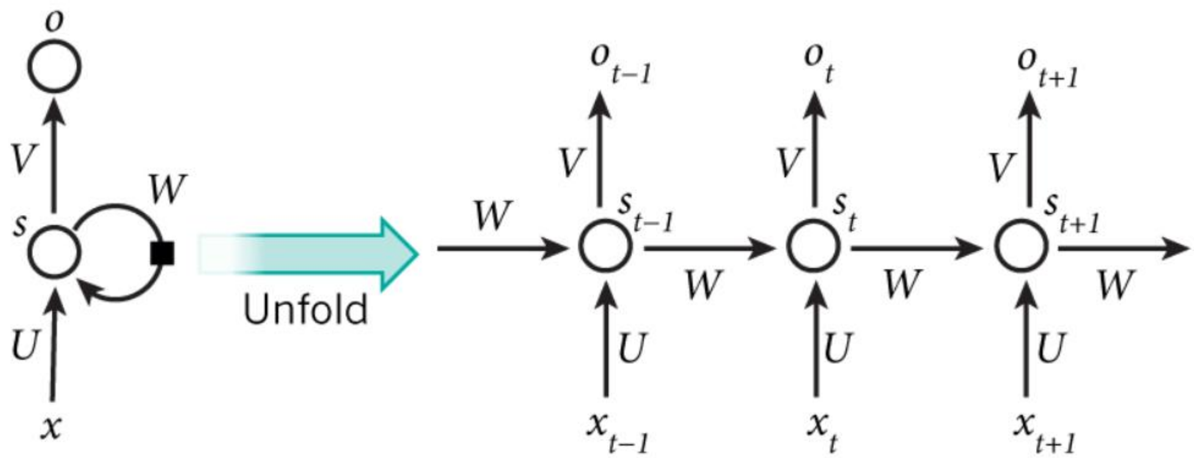

Figure 4.4: RNN Structure [70].

The figure 4.5 above shows an RNN unpacking into a full network.

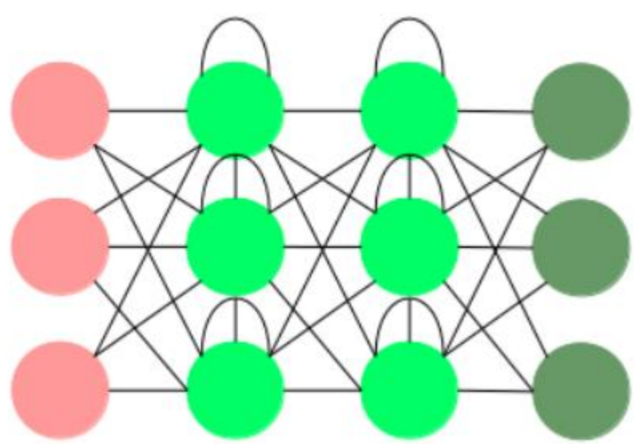

Figure 4.5: RNN Process 1 .

Bidirectional RNNs (Bidirectional RNNs): It is based on the idea that outputs at time t may depend on future items as well as on previous items in the queues. For example, you want to look at both left and right content to guess a missing word in a string. Bidirectional RNNs are pretty straightforward. These are just two RNNs stacked on top of each other. The outputs are then calculated based on the latent state of both RNNs.

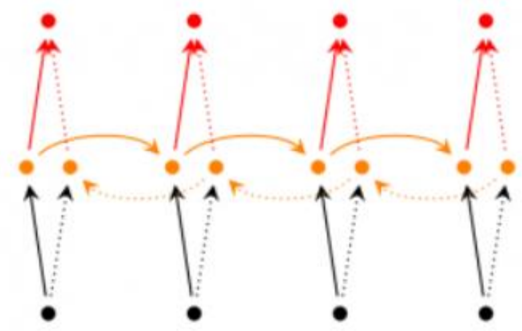

Figure 4.6: RNN Process 2 .

Deep (Bidirectional) RNNs (Deep RNNs): Similar to Bidirectional RNNs, they consist of multiple layers only in time step. In practice this gives us a higher learning capacity (but also needs a lot of training data).

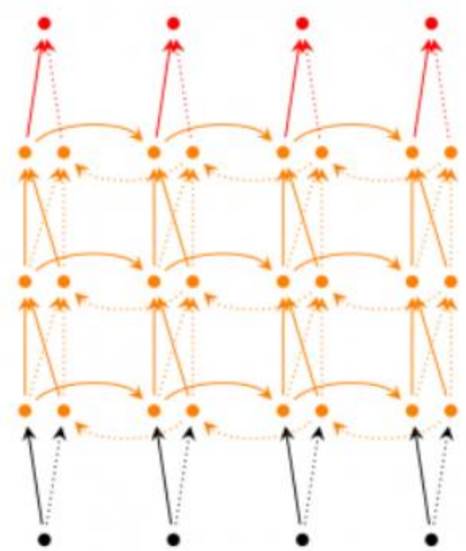

Figure 4.7: RNN Process 3.

4.4 A CONCRETE COMPRESSIVE STRENGTH PREDICATION MODEL

In this section, new compressive strength predication method presented which PSO applied to optimize the structure of the RNN. The aim of this study is to predicate the value of the compressive strength of the concrete in minimum processing time with accurate results. The properties of the concrete is first analysed by the RNN model to learn the formulation of the data. The mean square error (MSE) is calculated for the method RNN. The PSO applied to optimize the performance of the RNN by trying to reduce the MSE by updating the W and b which are the critical parameters of the RNN. The flowchart of the proposed method presented in the Figure 4.8.

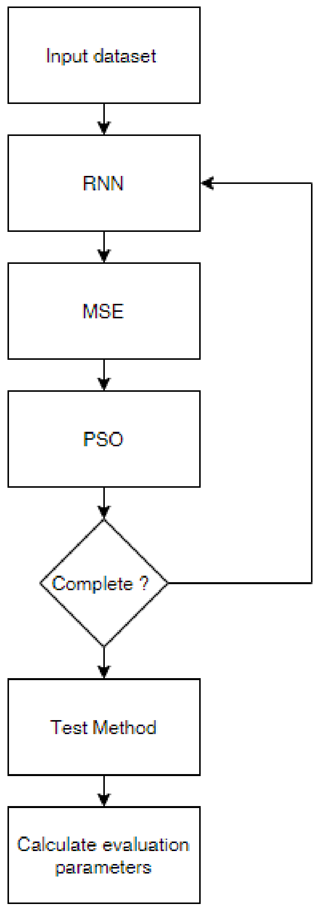

Figure 4.8: Flowchart of the proposed method.

The presented model developed using MATLAB. The presented application read the data from excel sheets as shown in Figure 4.9.

```
XTrain = xlsread('Train.xlsx',1,'A1:H7904');
```

Figure 4.9: Read train data from excel

Furthermore, the test data read by using the same command to test the model as shown in the Figure 4.10.

```
YTest= xlsread('Test.xlsx',1,'I1:I45');
```

Figure 4.10: Read test data from excel

The input size of the parameters are 8 parameters in each case. The output is regression type because the parameters are not discrete but continuous. The number of hidden units are represented in num. hidden. The layers of the RNN developed in this section which consist from LSTM and fully connected layers. The properties of the network presented in the Figure 4.11.

```
inputsize=8;

numberofoutput=1;

numhidden=10;

Layers=[sequenceInputLayer(inputsize)
    lstmLayer(numhidden)
    fullyConnectedLayer(numberofoutput)
    regressionLayer
    ];

options = trainingOptions('sgdm', ...
    'MaxEpochs', 1000,...
    'InitialLearnRate', 0.0001);
net=trainNetwork(XTrain,YTrain,Layers,options);
YPred= predict(net,XTest);
```

Figure 4.11: Network properties

The role of the PSO is to find best parameters of the RNN model weight and basis. The PSO also coded in MATLAB as shown in the below:

In the first step the parameters of the PSO are tuned

i. MaxIt=1000; Maximum Number of Iterations

ii. nPop=100; Population Size (Swarm Size)

iii. w=1; Inertia Weight

iv. wdamp=0.99; Inertia Weight Damping Ratio

v. c1=1.5; Personal Learning Coefficient

vi. c2=2.0; Global Learning Coefficient

then, in the second stage of the PSO execution the initialization of the algorithm start as shown in Figure 4.12.

```
empty_particle.Position=[];
empty_particle.Cost=[];
empty_particle.Velocity=[];
empty_particle.Best.Position=[];
empty_particle.Best.Cost=[];

particle=repmat(empty_particle,nPop,1);

GlobalBest.Cost=inf;
```

Figure 4.12: PSO initialization Function

In the last stage, the main loop of the PSO applied to complete the PSO algorithm and find the best weight and basis of the RNN as shown in the Figure 4.13.

```
for it=1:MaxIt

    for i=1:nPop

        % Update Velocity
        particle(i).Velocity = w*particle(i).Velocity ...
            +c1*rand(VarSize).*(particle(i).Best.Position-particle(i).Position)
            +c2*rand(VarSize).*(GlobalBest.Position-particle(i).Position);

        % Apply Velocity Limits
        particle(i).Velocity = max(particle(i).Velocity,VelMin);
        particle(i).Velocity = min(particle(i).Velocity,VelMax);

        % Update Position
        particle(i).Position = particle(i).Position + particle(i).Velocity;

        % Velocity Mirror Effect
        IsOutside=(particle(i).Position<VarMin | particle(i).Position>VarMax);
        particle(i).Velocity(IsOutside)=-particle(i).Velocity(IsOutside);
```

Figure 4.13: PSO main loop

4.5 DATASET

The dataset that used in this study is well known dataset that used in several studies and obtained from https://archive.ics.uci.edu/ml/datasets/Concrete+Compressive+Strength. The dataset that used to train and test the proposed method consist from 8 features (input) and 1 target (output). The dataset consist from 1030 sample with different values of inputs. The dataset type is regression type which contains continuous values in target which represented the concrete compressive strength value. The dataset features are: cement (kg in ^{3}), best furnace slag (kg in ^{3}), fly ash (kg in ^{3}), water (kg in ^{3}), superplasticizer (kg in ^{3}), coarse aggregate (kg in ^{3}), fine aggregate (kg in ^{3}), and age (days) and the output is concrete compressive strength MPa as output [1].

5. EXPERIMENTS AND DISSCUSION

5.1 RESULTS

Modelling is one way of creating a virtual representation of a real system that includes software and hardware. If the software components in this model are controlled by mathematical relationships, you can model this virtual representation under different conditions to see how it behaves. Modelling and simulation are particularly useful for hard-to-reproduce test environments that only use hardware prototypes, especially at the beginning of the design process when hardware is not available. By iterating between simulation and simulation, the design quality of the system can be improved at an early stage and errors discovered later in the design process can be reduced. By jointly evaluating the many factors that influence the compressive strength of concrete, a stronger concrete can be achieved even with much less cement than usual. Conversely, concrete that has been unknowingly prepared and laid can have much lower compressive strengths than expected. In this article, with the help of our tests, it was pointed out that the strength of concrete is not only dependent on the amount of cement, but also on other factors. Extremely careful and painstaking engineering is required when preparing, positioning, and curing concrete that must withstand stresses such as reinforcement.

5.2 DISCUSSIONS

In this section, several evaluation parameters are calculated for the proposed method and other machine learning techniques such as naïve bayes classifiers and neural network. The experimental results and calculated parameters show that the obtained results presented remarkable results and the our method RNN based PSO presented best results than other techniques.

5.2.1 Mean Error

Mean error is the average error between predicted values predicted by a machine learning model and actual values. Error in this context is the uncertainty in a measurement or the difference between the estimated value and the actual value. The RNN Based PSO presented 1,3 which is best than other techniques Neural Network 2,4, and Naïve Bayes Classifier presented only 2

ME. The Mean Error parameter show that the presented method is best than other techniques as shown in Figure 5.1.

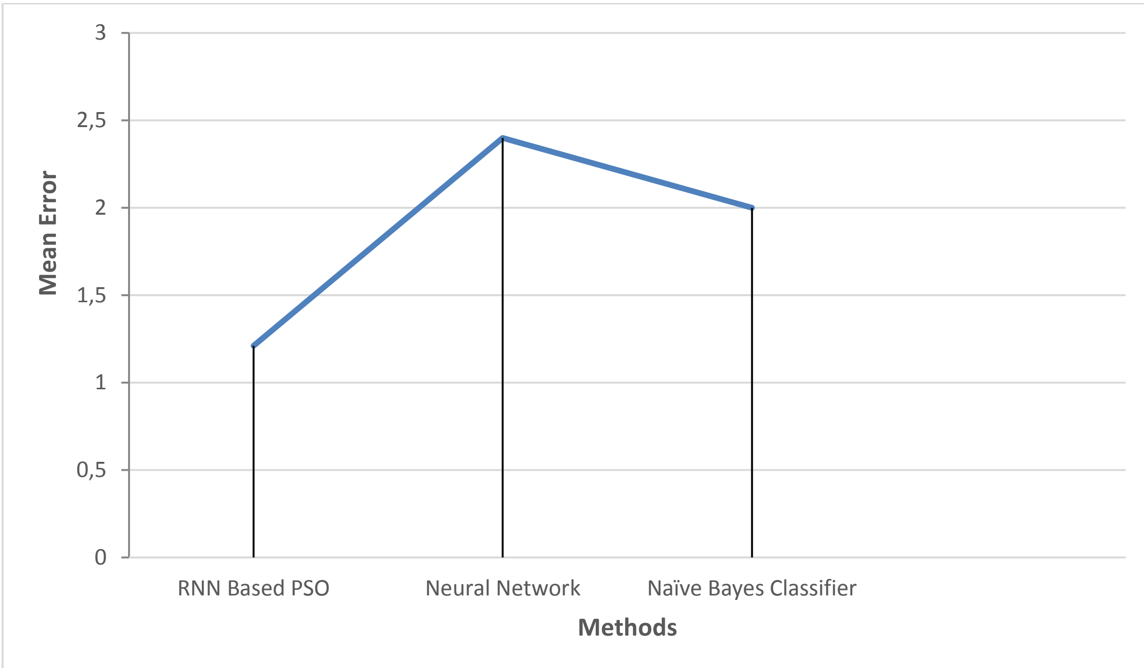

Figure 5.1: Mean Error.

5.2.2 Mean Percentage Error

It is the average percentage of the difference between the values predicted by a machine learning model and their actual values. MPE is mostly used for comparing predictive models. Positive and negative predictive errors can balance each other, as the actual values of the prediction errors rather than their absolute values are used when calculating the MPE value. Consequently, MPE can be used as a measure of bias in estimates. A disadvantage of this criterion is that if a single true value is zero, it is not defined [90].

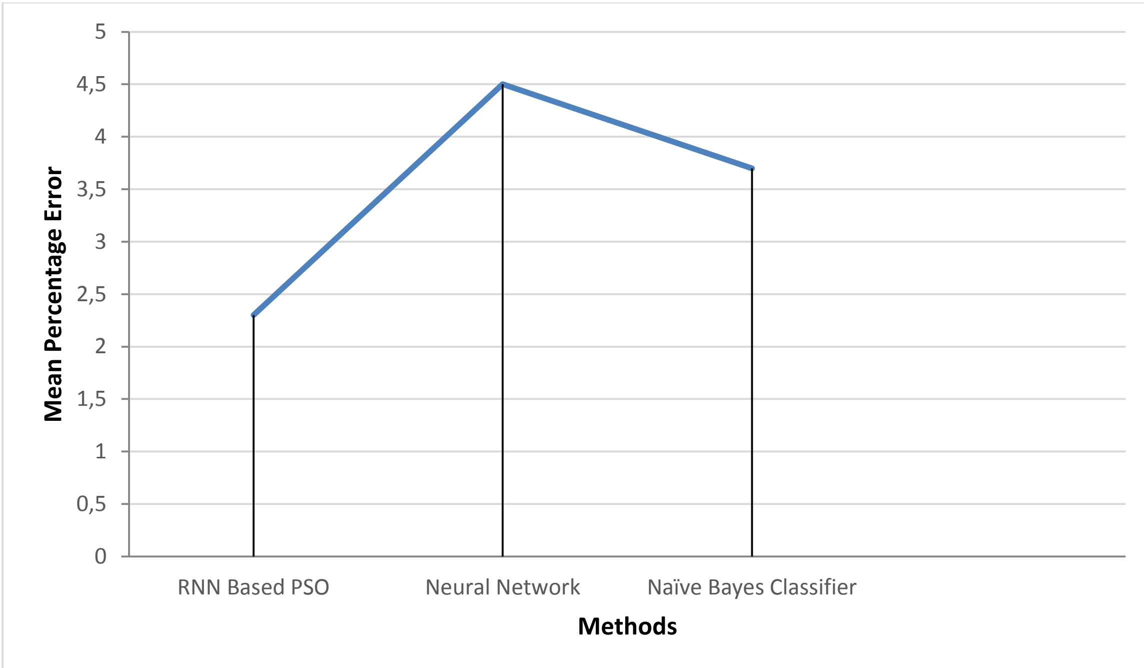

Figure 5.2: Mean Percentage Error.

5.2.3 Mean Squared Error

Simply, mean square error tells you how close a regression curve is to a set of points. MSE measures the performance of ML models that are forecasters, while forecasters that are always positive and have an MSE value close to zero may achieve better [92].

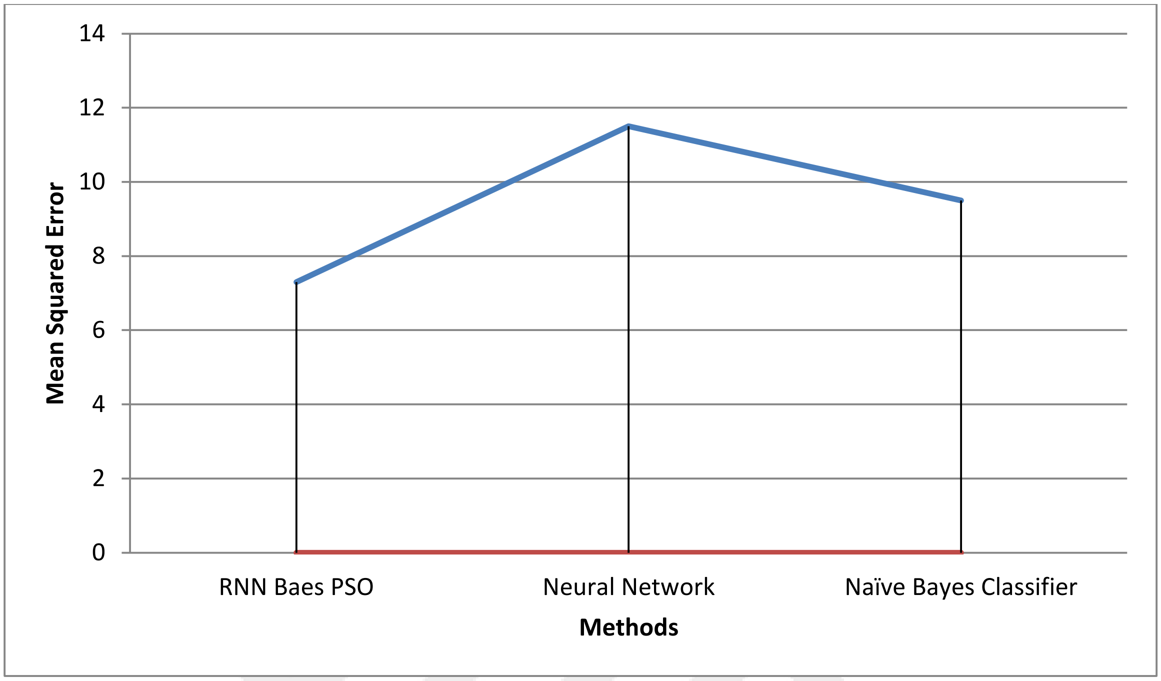

Figure 5.3: Mean Squared Error.

5.2.4 Root Mean Square Error

It is a quadratic metric that measures the size of the error and is often used to determine the distance between the predicted value of a predictor and the actual value of a machine learning model. Standard deviation of RMSE residuals. In other words, the residual is a measure of the distance between the regression line and the data points. The RMSE is a measure of the level of this residue. That is, it gives the data density around the row that best matches the data. The range of RMSE values is 0 to. Negative scores, i.e H. Predictors with lower values do better. Zero RMSE means the model is correct. The advantage of RMSE is that you are more likely to be penalized for serious misconduct and can adapt better to a particular situation. RMSE avoids using unnecessary absolute values in many mathematical calculations [93].

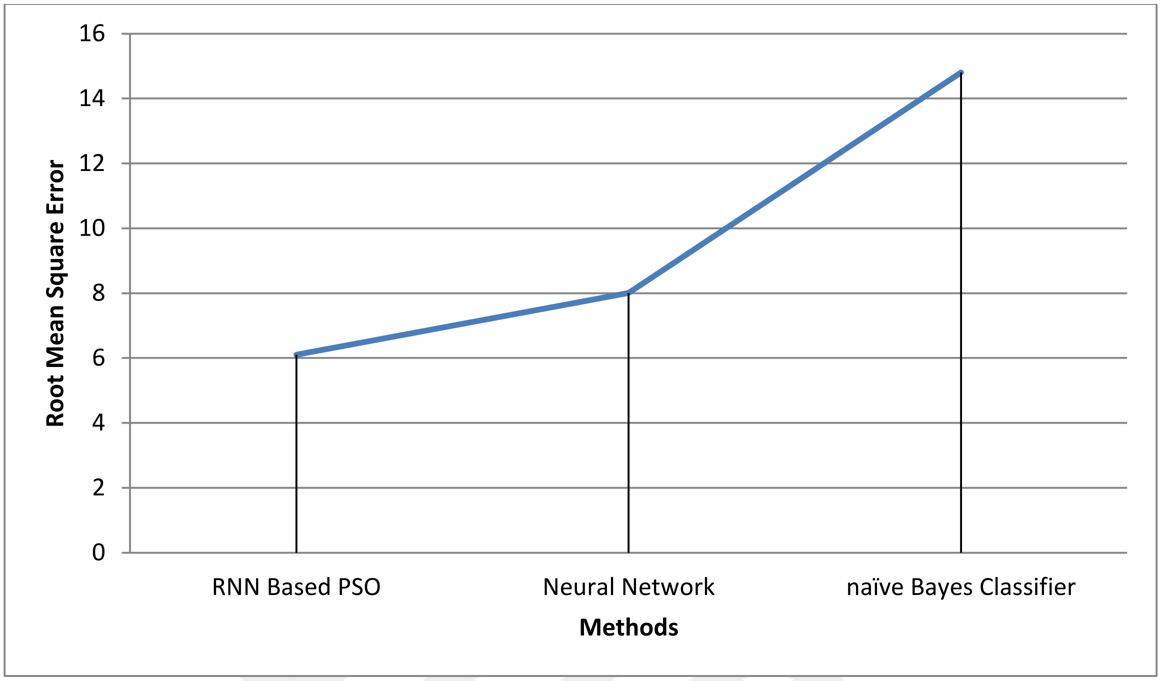

Figure 5.4: Root Mean Square Error.

Finally, the accuracy of the proposed model calculated and compared with other techniques to evaluate the results see Figure 5.5.

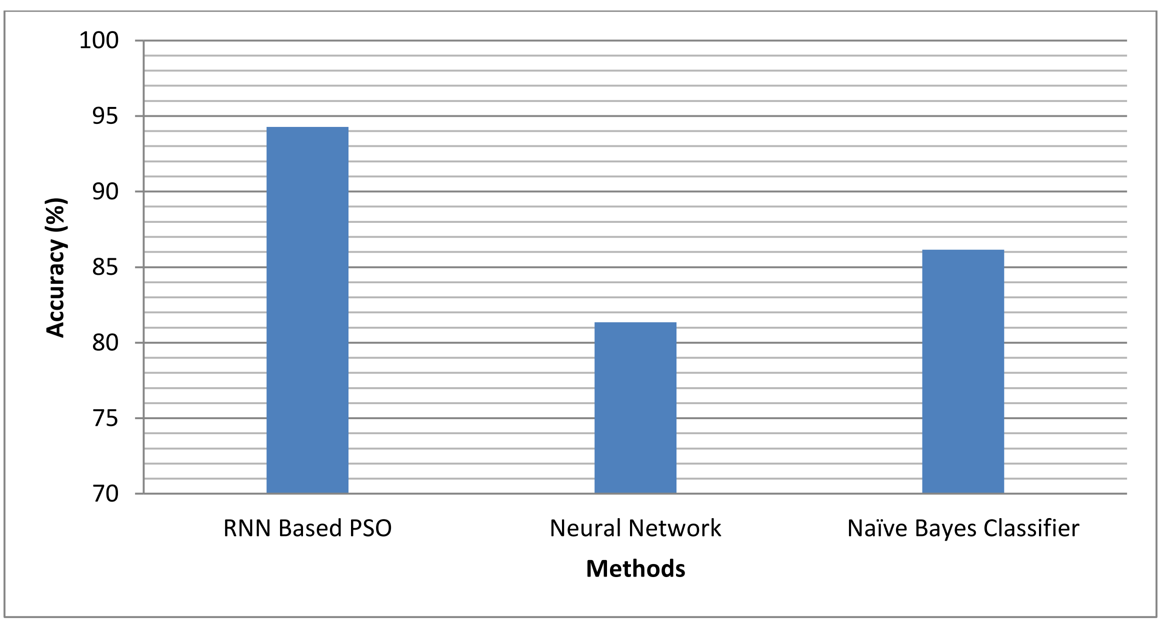

Figure 5.5: Accuracy

5.3 STATISTICS EXPLANATIONS

The statistical parameters that are calculated in this study lead to evaluate and prove the obtained results. The calculating more that one evaluation parameter lead to increase the robustness of the model. Because of the model is regression model than parameters such as Mean error, Mean Percentage Error, Mean Squared Error, and Root Mean Square Error. The RNN based PSO presented minimum Mean error which presented only 0.020500 which very low mean error rate. Furthermore, mean percentage error calculated for the model and presented lowest value 0.02190000 when compared with neural network 0.036982799 and naïve bayes 0.036982799.

Table 5.1: Statistical Parameters

Parameter	Techniques	Values
Mean error	Neural Network	0.020500
Mean error	Naïve Bayes	0.0219000
Mean error	RNN Based PSO	0.0119000
Mean Percentage Error	Neural Network	0.04190001900
Mean Percentage Error	Naïve Bayes	0.036982799
Mean Percentage Error	RNN Based PSO	0.02190000
Mean Squared Error	Neural Network	0.011190001900
Mean Squared Error	Naïve Bayes	0.0913861626
Mean Squared Error	RNN Based PSO	0.079823552
Accuracy	Neural Network	81.34
Accuracy	Naïve Bayes	86.15
Accuracy	RNN Based PSO	94.28

Moreover, the proposed model RNN Based PSO also presented the minimum Mean Squared Error which the error rate only 0.079823552 when compared with naïve bayes 0.0913861626 and neural network 0.011190001900. Then, the accuracy of the model calculated and presented the highest accuracy which presented 94.28 which mean highest true rate when compared with naïve bayes 86.15 and neural network 81.34. These results lead to that its possible to apply this model in real problems and applications to assist engineers and project managers in managing complex projects.

6. CONCLUSION

Concrete compressive strength is one of the most important properties as it is closely related to other properties of concrete. For this reason, many studies on the predetermination of concrete compressive strength have been carried out intensively recently.

Machine learning and data mining are successfully used in the estimation of concrete strengths. In the last years deep learning which is the new version of machine learning playing critical role in several engineering problems. The RNN that is one of the best deep learning techniques applied to several regression problems. The RNN applied to learn the predication of concrete compressive strength which is important civil engineering problem and require high experience to estimate it manually.

Efficient method presented combined RNN with PSO to predicate the Concrete Compressive Strength. Artificial recurrent neural network (RNN) architecture used in the field of deep learning. The RNN is applied in regression and classification problems effectively. The PSO applied to optimize the structure of the RNN by optimizing weight and basis of the model. The obtained results compared with several studies presented in this filed and show superior.

These can be models for a particular problem, when it is believed that there is a validation gap, or when a particular methodology is not available. In order to predict the properties of concrete with high reliability, traditional and innovative models can be replaced by models with artificial intelligence instead of expensive experimental research. As this study shows, Computational Intelligence models can be used successfully, Computational Intelligence models can be used successfully. The prediction of the average billing agreement for this maximum degree of pressure agreement is evaluated experimentally on the concrete samples used.

After analyzing the results that are obtained in this study, the author can presented number of notes that can assist the researchers in the future studies. We advise the researcher to apply other new deep learning techniques to predicate the concrete compressive strength. Furthermore, feature extraction techniques also advised to apply to this problem which an effect features will removed. We advise also, to apply the presented model to the other concrete compressive strength datasets to evaluate and prove the obtained results.

REFERENCES

[1] Yeh IC. “UCI Machine Learning Repository: Concrete Compressive Strength Data Set” http://archive.ics.uci.edu/ml/datasets/Concrete+Compr essive+Strength (20.03.2014).

[2] Yeh IC. “Modeling of Strength of High-Performance Concrete Using Artificial Neural Networks”. Cement and Concrete Research, 28(12), 1797-1808, 1998.

[3] Hong-Guang N, Ji-Zong W. “Prediction of Compressive Strength of Concrete by Neural Networks”. Cement and Concrete Research, 30(8), 1245-1250, 2000.

[4] Seyhan AT, Tayfur G, Karakurt M, Tanoğlu M. “Artificial Neural Network (ANN) Prediction of Compressive Strength of VARTM Processed Polymer Composites”. Computational Materials Science, 34(1), 99-105, 2005.

[5] Gupta R, Kewalramani MA, Goel A. “Prediction of Concrete Strength Using Neural-Expert System”. Journal of Materials in Civil Engineering, 18(3), 462-466, 2006.

[6] Topcu IB, Sarıdemir M. “Prediction of Compressive Strength of Concrete Containing Fly Ash Using Artificial Neural Networks and Fuzzy Logic”. Computational Materials Science, 41(3), 305-311, 2008.

[7] Raghu Prasad BK, Eskandari H, Venkatarama Reddy BV. “Prediction of Compressive Strength of SCC and HPC with High Volume fly ash Using ANN”. Construction and Building Materials, 23(1), 117-128, 2009.

[8] Khan MI. “Predicting Properties of High Performance Concrete Containing Composite Cementitious Materials Using Artificial Neural Networks”. Automation in Construction, 22, 516-524, 2012.

[9] Atıcı U. “Prediction of the Strength of Mineral Admixture Concrete Using Multivariable Regression Analysis and an Artificial Neural Network”. Expert Systems with Applications, 38(8), 9609-9618, 2011.

[10] Nikoo M, Zarfam P, Sayahpour H. “Determination of Compressive Strength of Concrete Using Self Organization Feature Map (SOFM)”. Engineering with Computers, 31(1), 113-121, 2015.

[11] Fazel-Zarandi MH, Türksen IB, Sobhani J, Ramezanianpour AA. “Fuzzy Polynomial Neural Networks for Approximation of the Compressive Strength of Concrete”. Applied Soft Computing, 8(1), 488-498, 2008.

[12] Yeh IC, Lien LC. “Knowledge Discovery of Concrete Material Using Genetic Operation Trees”. Expert Systems with Applications, 36(3), 5807–5812, 2009.

[13] Cheng MY, Peng HS, Wu YW, Chen TL. “Estimate at Completion for Construction Projects Using Evolutionary Support Vector Machine Inference Model”. Automation in Construction, 19(5), 619–629, 2010.

[14] Wang YR, Yu CY, Chan HH. “Predicting Construction Cost and Schedule Success Using Artificial Neural Networks Ensemble and Support Vector Machines Classification Models”. International Journal of Project Management, 30(4), 470-478, 2012.

[15] Cheng MY, Chou JS, Roy AFV, Wu YW. “High-performance Concrete Compressive Strength Prediction using TimeWeighted Evolutionary Fuzzy Support Vector Machines Inference Model”. Automation in Construction, 28, 106–115, 2012.

[16] Cheng MY, Firdausi PM, Prayogo D. “High-performance Concrete Compressive Strength Prediction using Genetic Weighted Pyramid Operation Tree (GWPOT)”. Engineering Applications of Artificial Intelligence. 29, 104-113, 2014.

[17] Chou JS, Chiu CK, Farfoura M, Al-Taharwa I. “Optimizing the Prediction Accuracy of Concrete Compressive Strength Based on A Comparison of Data-mining Techniques”. Journal of Computing in Civil Engineering, 25(3), 242-253, 2011.

[18] Abraham A, Philip NS, Saratchandran P. “Modeling Chaotic Behavior of Stock Indices Using Intelligent Paradigms”. Neural, Parallel & Scientific Computations, 11(1-2), 143- 160, 2003.

[19] Huang S, Wu T. “Integrating GA-based Time-scale Feature Extractions with SVMs for Stock Index Forecasting”. Expert Systems with Applications, 35(4), 2080-2088, 2008.

[20] Bezobrazov, A. Sachenko, M. Komar and V. Rubanau, "Artificial immune system for Android OS," 2015 IEEE 8th International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), Warsaw, 2015, pp. 403-407, doi: 10.1109/IDAACS.2015.7340767.

[21] Rajalakshmi and N. Anusha, "Sensor based application for malware detection in android OS(Operating System) devices," 2017 International Conference on Information Communication and Embedded Systems (ICICES), Chennai, 2017, pp. 1-6, doi: 10.1109/ICICES.2017.8070722.

[22] Ayyasamy, "Survey on Android application advancement and security," 2015 Seventh International Conference on Advanced Computing (ICoAC), Chennai, 2015, pp. 1-4, doi: 10.1109/ICoAC.2015.7562799.

[23] A. Utku and İ. A. Doğru, "Malware detection system based on machine learning methods for Android operating systems," 2017 25th Signal Processing and Communications Applications Conference (SIU), Antalya, 2017, pp. 1-4, doi: 10.1109/SIU.2017.7960231.

[24] P. G. A. A. Putra, E. Sediyono and A. Setiawan, "E-land design of mobile application for land information system using Android-based Google Maps API V2," 2017 International Conference on Innovative and Creative Information Technology (ICITech), Salatiga, 2017, pp. 1-5, doi: 10.1109/INNOCIT.2017.8319145.

[25] Ho Jun Myeong, Yeo Hun Yoon, Nam Ju Cha, W. Y. Du and Dong Hwan Kim, "User tracking of an educational robot with android operating system based robot platform," 2012 9th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), Daejeon, 2012, pp. 132-135, doi: 10.1109/URAI.2012.6462951.

[26] M. Kovacev, K. Lazic, N. Jovanovic, A. Stefanovic and I. Petrovic, "Implementation of Disaster recovery agent within Android based set-top box," 2013 IEEE Third International Conference on Consumer Electronics ¿ Berlin (ICCE-Berlin), Berlin, 2013, pp. 1-3, doi: 10.1109/ICCE-Berlin.2013.6697996.

[27] N. T. Cam, T. Nguyen, K. Nguyen, T. Nguyen and V. Pham, "Detect Malware in Android Firmware Based on Distributed Network Environment," 2019 IEEE 19th International Conference on Communication Technology (ICCT), Xi'an, China, 2019, pp. 1566-1570, doi: 10.1109/ICCT46805.2019.8947099.

[28] M. Dinić, A. Rikalo, A. Marković and P. Jovanović, "TLB maintenance optimization in android emulator for mips platform," 2016 24th Telecommunications Forum (TELFOR), Belgrade, 2016, pp. 1-4, doi: 10.1109/TELFOR.2016.78188.

[29] K. Wang, Y. Hou and Y. Xu, "Design and Implementation of Remote Control System between Android Platform," 2016 International Conference on Information System and Artificial Intelligence (ISAI), Hong Kong, 2016, pp. 143-147, doi: 10.1109/ISAI.2016.0039.

[30] A. Heryana, E. Nugraheni, B. Kusumo, A. F. Rojie and B. Setiadi, "Applying agile methods in designing an earthquake and landslide early warning system application for Android," 2017 International Conference on Computer, Control, Informatics and its Applications (IC3INA), Jakarta, 2017, pp. 80-84, doi: 10.1109/IC3INA.2017.8251744.

[31] O. C. Novac, M. Novac, C. Gordan, T. Berczes and G. Bujdosó, "Comparative study of Google Android, Apple iOS and Microsoft Windows Phone mobile operating systems," 2017 14th International Conference on Engineering of Modern Electric Systems (EMES), Oradea, 2017, pp. 154-159, doi: 10.1109/EMES.2017.7980403.

[32] C. Yuan, Y. Yue, X. Li and L. Feng, "Performance analysis and optimization of inter process communication in Android," 2016 6th International Conference on Electronics Information and Emergency Communication (ICEIEC), Beijing, 2016, pp. 297-300, doi: 10.1109/ICEIEC.2016.7589742.

[33] Arshad, M. A. Shah, A. Wahid, A. Mehmood, H. Song and H. Yu, "SAMADroid: A Novel 3-Level Hybrid Malware Detection Model for Android Operating System," in IEEE Access, vol. 6, pp. 4321-4339, 2018, doi: 10.1109/ACCESS.2018.2792941.

[34] E. Türk and S. Arslan, "Boot time optimization for Android-based embedded systems," 2017 International Conference on Computer Science and Engineering (UBMK), Antalya, 2017, pp. 1004-1008, doi: 10.1109/UBMK.2017.8093416.

[35] A. Yao, P. Sun, S. Yang and D. Li, "Evolution of Function-Call Network Reliability in Android Operating System," in IEEE Transactions on Circuits and Systems I: Regular Papers, vol. 67, no. 4, pp. 1264-1275, April 2020, doi: 10.1109/TCSI.2020.2972995.

[36] Z. D. Patel, "Malware Detection in Android Operating System," 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), Greater Noida (UP), India, 2018, pp. 366-370, doi: 10.1109/ICACCCN.2018.8748512.

[37] M. Cajic, B. Brkic and M. Veinovic, "System of assessment security for Android operating system," 2012 20th Telecommunications Forum (TELFOR), Belgrade, 2012, pp. 1448-1451, doi: 10.1109/TELFOR.2012.6419491.

[38] M. A. Dar, S. Nisar Bukhari and U. I. Khan, "Evaluation of Security and Privacy of Smartphone Users," 2018 Fourth International Conference on Advances in Electrical, Electronics, Information, Communication and Bio-Informatics (AEEICB), Chennai, 2018, pp. 1-4, doi: 10.1109/AEEICB.2018.8480914.

[39] F. Heriniaina, "CoSINcheck to protect users from installing potentially harmful Android applications," 2017 Third International Conference on Mobile and Secure Services (MobiSecServ), Miami Beach, FL, 2017, pp. 1-5, doi: 10.1109/MOBISECSERV.2017.7886564.

[41] R. Manoharan and S. Chandrakala, "Android OpenCV based effective driver fatigue and distraction monitoring system," 2015 International Conference on Computing and Communications Technologies (ICCCT), Chennai, 2015, pp. 262-266, doi: 10.1109/ICCCT2.2015.7292757.

[40] M. Kovacevic, B. Kovacevic, B. Pavlovic and N. Bandic, "Visualization of interactive digital television services content in Android operating system," 2012 20th Telecommunications Forum (TELFOR), Belgrade, 2012, pp. 1357-1360, doi: 10.1109/TELFOR.2012.6419469.

[42] R. Hunt, "Security testing in Android networks - A practical case study," 2013 19th IEEE International Conference on Networks (ICON), Singapore, 2013, pp. 1-6, doi: 10.1109/ICON.2013.6781950.

[43] O. C. Novac, I. Mureşan, M. C. Novac, M. P. Ursu, M. Oproescu and C. M. Dindelegan, "Development of a Weather Mobile Application in Android Operating System," 2019 11th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Pitesti, Romania, 2019, pp. 1-5, doi: 10.1109/ECAI46879.2019.9042040.

[44] S. Agarwal and N. Agarwal, "Interfacing of robot with android app for to and fro communication," 2016 Second International Innovative Applications of Computational Intelligence on Power, Energy and Controls with their Impact on Humanity (CIPECH), Ghaziabad, 2016, pp. 222-226, doi: 10.1109/CIPECH.2016.7918771.

[45] Guha, S., Yau, S. S., & Buduru, A. B. (2016, August). Attack detection in cloud infrastructures using artificial neural network with genetic feature selection. In Dependable, Autonomic and Secure Computing, 14th Intl Conf on Pervasive Intelligence and Computing, 2nd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech), 2016 IEEE 14th Intl C (pp. 414-419). IEEE.

[46] Nguyen, K. K., Hoang, D. T., Niyato, D., Wang, P., Nguyen, D., & Dutkiewicz, E. (2018, April). Cyberattack detection in mobile cloud computing: A deep learning approach. In Wireless Communications and Networking Conference (WCNC), 2018 IEEE (pp. 1-6). IEEE.

[47] F. Gao, L. Leng and X. Fu, "Palmprint Verification System with Dual-Line-Single-Point Assistance on Android Mobile Devices," 2018 4th Annual International Conference on Network and Information Systems for Computers (ICNISC), Wuhan, China, 2018, pp. 437-441, doi: 10.1109/ICNISC.2018.00095.

[48] K. Nagata, Y. Nakamura, S. Nomura and S. Yamaguchi, "Measuring and Improving Application Launching Performance on Android Devices," 2013 First International Symposium on Computing and Networking, Matsuyama, 2013, pp. 636-638, doi: 10.1109/CANDAR.2013.116.

[49] E. G. d. Oliveira, M. S. F. d. Oliveira, N. R. Neto, F. d. P. Soldati and T. L. C. Nassur, "Development and evaluation of a mobile educational application to support teaching of management of process in Operating Systems," 2020 IEEE 20th International Conference on Advanced Learning Technologies (ICALT), Tartu, Estonia, 2020, pp. 19-21, doi: 10.1109/ICALT49669.2020.00012.

[50] S. N. Verzynov, I. V. Bochkarev and V. R. Khramshin, "Development of Line Locator Software Component for Mobile Operating Systems," 2020 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), Sochi, Russia, 2020, pp. 1-5, doi: 10.1109/ICIEAM48468.2020.9112019.

[51] Nemet, S. Radovanović, R. Simikić, I. Papp and T. Novković, "Adaptive TR-069 system service for Android-based consumer electronic devices," 2013 IEEE Third International Conference on Consumer Electronics ¿ Berlin (ICCE-Berlin), Berlin, 2013, pp. 258-260, doi: 10.1109/ICCE-Berlin.2013.6697980.

[52] Mu, Z. Tan and G. Zhu, "Android-Based Order Recommender System," 2018 International Conference on Robots & Intelligent System (ICRIS), Changsha, 2018, pp. 258-261, doi: 10.1109/ICRIS.2018.00073.

[53] V. Bjelić, N. Lukić, S. Kovačević and M. Vucelja, "Improving teletext support for set top box based on Android operating system," 2013 21st Telecommunications Forum Telfor (TELFOR), Belgrade, 2013, pp. 995-998, doi: 10.1109/TELFOR.2013.6716399.

[54] Kumar and R. M., "Location Based Parental Control-Child Tracking App Using Android Mobile Operating System," 2018 4th International Conference on Computing Communication and Automation (ICCCA), Greater Noida, India, 2018, pp. 1-4, doi: 10.1109/CCAA.2018.8777612.

[55] H. Shang, Q. Zhang, M. Jin, W. Wang, J. Zhu and Q. Kong, "A portable pulse signal acquiring and monitoring system based on Android platform," 2013 IEEE International Conference on Bioinformatics and Biomedicine, Shanghai, 2013, pp. 226-227, doi: 10.1109/BIBM.2013.6732679.

[56] E. Zhang, S. Peng and Y. Zhai, "Design and Application Development of the Camps Navigation System Based on ArcGIS Runtime SDK for Android : ——Taking the Yunnan Normal University as an example," 2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chengdu, China, 2019, pp. 1262-1266, doi: 10.1109/IAEAC47372.2019.8997730.

[57] Y. Zhao, Z. Yang, C. Song and D. Xiong, "Vehicle dynamic model-based integrated navigation system for land vehicles," 2018 25th Saint Petersburg International Conference on Integrated Navigation Systems (ICINS), St. Petersburg, 2018, pp. 1-4, doi: 10.23919/ICINS.2018.8405846.

[58] M. Ivankovic and I. Basicevic, "Additional Multimedial Screen for Control of a Hbbtv Application with the use of Android Operating System," 2018 26th Telecommunications Forum (TELFOR), Belgrade, 2018, pp. 420-425, doi: 10.1109/TELFOR.2018.8611871.

[59] S. Iqbal, A. Yasin and T. Naqash, "Android (Nougats) security issues and solutions," 2018 IEEE International Conference on Applied System Invention (ICASI), Chiba, 2018, pp. 1152-1155, doi: 10.1109/ICASI.2018.8394488.

[60] D. Hongyu, L. Lizong, Q. Dixin and O. Baibing, "Design of College Canteen Ordering System Based on Cortex-A9 and Android," 2020 International Workshop on Electronic Communication and Artificial Intelligence (IWECAI), Shanghai, China, 2020, pp. 179-183, doi: 10.1109/IWECAI50956.2020.00043.

[61] Senirkentli, G.B.; Ekinci, F.; Bostanci, E.; Güzel, M.S.; Dağli, Ö.; Karim, A.M.; Mishra, A. Proton Therapy for Mandibula Plate Phantom. *Healthcare* **2021**, *9*, 167. https://doi.org/10.3390/healthcare9020167.

[62] Xu, Ning Su, Rujing Wang and Liangtu Song, "A novel variable rate fertilization system based on the Android platform," 2015 IEEE International Conference on Progress in Informatics and Computing (PIC), Nanjing, 2015, pp. 395-398, doi: 10.1109/PIC.2015.7489876.

[63] Karimi, A.M.; Çelebi, F.V.; Mohammed, A.S. Software Development for Blood Disease Expert System. Lect. Notes Softw. Eng. 2016, 4, 179–183.

[64] A. M. Karim, M. S. Güzel, M. R. Tolun, H. Kaya, and F. V. Çelebi, ‘‘A new framework using deep auto-encoder and energy spectral density for medical waveform data classification and processing,’’ Biocybernetics Biomed. Eng., vol. 39, no. 1, pp. 148–159, Jan. 2019.

[65] Karim A.M., Mishra A. (2022) Novel COVID-19 Recognition Framework Based on Conic Functions Classifier. In: Garg L., Chakraborty C., Mahmoudi S., Sohmen V.S. (eds) Healthcare Informatics for Fighting COVID-19 and Future Epidemics. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-72752-9_1.

[66] A. M. Karim, M. S. Güzel, M. R. Tolun, H. Kaya, and F. V. Çelebi, ‘‘A new generalized deep learning framework combining sparse autoencoder and Taguchi method for novel data classification and processing,’’ Math. Problems Eng., vol. 2018, May 2018, Art. no. 3145947. doi: 10.1155/2018/3145947.

[67] Karim, A., KARAL, Ö. and ÇELEBİ, F. (2019). A deep learning approach to EEG based epilepsy seizure determination. [online] Available at: https://www.researchgate.net/publication/304405331_A_deep_learning_approach_to_EEG_based_epilepsy_seizure_determination [Accessed 30 Sep. 2019].

[68] K. Nagata, Y. Nakamura, S. Nomura and S. Yamaguchi, "Measuring and Improving Application Launching Performance on Android Devices," 2013 First International Symposium on Computing and Networking, Matsuyama, 2013, pp. 636-638, doi: 10.1109/CANDAR.2013.116.

[69] E. G. d. Oliveira, M. S. F. d. Oliveira, N. R. Neto, F. d. P. Soldati and T. L. C. Nassur, "Development and evaluation of a mobile educational application to support teaching of management of process in Operating Systems," 2020 IEEE 20th International Conference on Advanced Learning Technologies (ICALT), Tartu, Estonia, 2020, pp. 19-21, doi: 10.1109/ICALT49669.2020.00012.

[70] Karim, A. M., Güzel, M. S., Tolun, M. R., Kaya, H., & Çelebi, F. V. (2019). A new framework using deep auto-encoder and energy spectral density for medical waveform data

classification and processing. Biocybernetics and Biomedical Engineering, 39(1), 148-159. doi:10.1016/j.bbe.2018.11.004.