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EDITORIAL

Dear Colleagues,

Academic journals are one of the most essential elements of the academy, where researchers announce their findings to the scientific world. Therefore, an academic journal should have continuity, stability, and quality characteristics.

I am honored and happy to greet you with the first issue of our journal, "Journal of Computer & Electrical and Electronics Engineering Sciences," which we set out to contribute to the scientific world with the great sense of responsibility brought by academic publishing and quality publishing.

Our journal, which aims to publish original and high-quality studies in Computer Engineering and Electrical-Electronics Engineering, started its publication to announce new studies and original research in the field to the scientific world.

Our journal, which evaluates the principle of blind refereeing, is also sensitive to protecting personal data and ethical concerns.

Our journal, which we plan to be published as two issues a year, will climb the steps of quality in academic publishing one by one. My belief comes from our publishing team, who work voluntarily for this job. As the editor-in-chief, I would like to thank this beautiful team dedicated to science.

We know that with each subsequent issue, our intensity will increase; However, with our commitment to science, we will continue to offer you the latest studies as a team without compromising our principles. I want to express my sincere gratitude and respect to you, our readers, writers, referees, and our publishing team working with great devotion; I sincerely look forward to your comments and suggestions for improving our journal.

Fuat Turk, PhD
Editor-in-Chief

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ORIGINAL ARTICLE

REVIEW

Journal of
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Original Article

DOI: 10.51271/JCEEES-0001

Convolutional neural network for pothole detection in different road and weather conditions

Qusai Gazawy[1], Selim Buyrukoğlu[1], Yıldıran Yılmaz[2]

[1]Department of Computer Engineering, Faculty of Engineering, Çankırı Karatekin University, Çankırı, Turkey
[2]Department of Computer Engineering, Faculty of Engineering and Architecture, Recep Tayyip Erdogan University, Rize, Turkey

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Corresponding Author: Selim Buyrukoğlu, sbuyrukoglu@karatekin.edu.tr

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ABSTRACT

Aims: To propose a deep learning algorithm for pothole detection and compare the performance of Sigmoid and Softmax activation functions in the creation of Convolutional Neural Network (CNN) algorithms.

Methods: Three different datasets were used to justify the robustness of the CNN model in detecting dry and wet potholes. The CNN algorithms were created separately using the Sigmoid and Softmax activation functions.

Results: The CNN algorithm using the Sigmoid function achieved higher accuracy scores than the CNN algorithm using the Softmax function. Specifically, the Sigmoid algorithm achieved accuracy scores of 91%, 96%, and 83% over datasets 1, 2, and 3, respectively, while the Softmax algorithm achieved scores of 81%, 96%, and 85% over the same datasets.

Conclusion: The results of this study suggest that the CNN algorithm using the Sigmoid activation function is more robust and effective in detecting pothole images compared to the CNN algorithm using the Softmax activation function.

Keywords: Potholes detection, CNN, rebostness, activation function

INTRODUCTION

Because of the large number of daily activities, most people are required to use their vehicles almost every day. Some countries have bad road conditions which need road maintenance. The accident rates are increasing continuously because of potholes on the roads. Not only car accidents, but also motorcycle accidents can have a higher chance of resulting in death than car accidents. The potholes on the roads should be detected and then repaired to reduce the deaths. However, this is not an easy task and is expensive. The use of motorcycles in Indonesia is pretty much and so the motorcycle accident rate is high compared to the other countries in the world (Saputra, 2017; Wibowo, 2010). In 2020, in the United States of America, motorcycle riders have been involved in crashes more than any other motor vehicle, 27% for motorcycles, 23% for passenger cars, 19% for light trucks, and 3% for trucks (Injury Facts, 2020).

In the literature, different studies about pothole detection were implemented. In a study by Chen, Yao, and Gu (2020), a new method to detect potholes based on a location-aware convolutional neural networks system is implemented and they have obtained precision and recall scores of 95.2% and 92.0% respectively. Hanif, Lie, Astuti, and Tan (2020) implemented a CNN-based model to detect potholes to overcome the limitations of various expensive sensors. They have obtained accuracy, sensitivity, and F-measure of 99.02%, 99.03%, and 98.33% respectively. Ping, Yang, and Gao (2020) created a pothole detection system using 4 models which are YOLO, V3, SSD, HOG with SVM, and Faster R-CNN. They have obtained accuracy scores for YOLO, SSD, HOG and Faster R-CNN of 82%, 80%, 27% and 74% respectively. Maeda, Sekimoto, Seto, Kashiyama, and Omata (2018) employed a CNN algorithm for the detection of road damage using the images obtained by phones. The proposed CNN algorithm achieved to provide convincing statistical scores in the detection of road damages. Even if the above-mentioned studies achieved to provide convincing statistical scores based on their aims and objectives, there is an important limitation. The limitation is that they have not focused on the measurement of the robustness of the proposed approaches. Thus, in the present study, we aim to classify pothole detection in roads using different three publicly available datasets. The contribution of this study is the creation of a robust model to classify pothole detection using three different datasets. Our model detects pothole images that are taken from a mounted camera inside the vehicle or images that are taken from a cell phone on the road. Also, it detects potholes in different seasons i.e. summer and winter, and different road conditions like paved and unpaved roads. Detailed information about the proposed model is presented in Chapter 2 (also **Figure 1** shows the general framework of the model).

This paper is organized as follows. Section 2 gives information about the materials and methods including the data obtaining, data pre-processing, and architecture of the Convolutional Neural Network (CNN). Then, Section 3 evaluates the efficiency of the employed CNN algorithms for pothole detection. In the end, Section 4 presents the conclusion and future directions.

METHODS

Figure 1 presents the proposed pothole detection approach in different road and weather conditions. This approach is treated under three headings: Dataset, Pre-processing, and architecture of the Convolutional Neural Network (CNN).

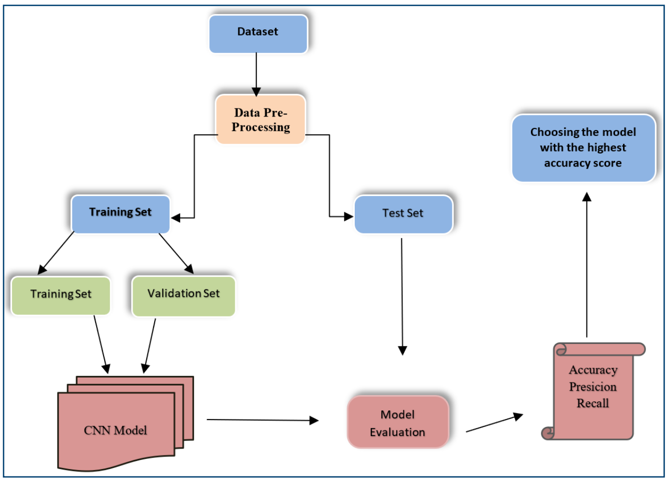

Figure 1. Proposed pothole detection approach in different road and weather conditions.

Dataset Description and Image Pre-processing

Three different datasets have been used in this study. The first dataset includes 500 samples obtained from Maeda et al. (2018) and Nienaber et al. (2015). The second dataset consists of 681 samples obtained from Kumar (n.d.). Finally, the third dataset has 650 samples obtained from Bhutad and Patil (2022). **Figure 2** presents an image from each dataset separately.

Figure 2. Example images used in this study.

Image Pre-Processing

The original pothole images have high resolution and using the original pothole image may take more computational time. Thus, the images are resized from 3680 x 2760 resolution to 64 x 64 resolution for faster processing and optimal segmentation. Also, the images are rescaled to 0-1 so the network tends to yield better results when the inputs are normalized. Moreover, the images are split into training (72%), validation (18%), and test (10%) images.

The architecture of the Convolutional Neural Network

The structure of the used CNN is shown in **Figure 3**, and this section provides information about the Convolutional Layer, Pooling Layer, and Fully Connected Layer (FC Layer) (LeCun, Bengio, & Hinton, 2015). Convolutional Layer is used to reduce the dimensionality of the image. In our model we have 2 convolutional layers, each layer has 32 filters which consist of a 64x64 matrix, it will create 64x64 box in our images that evolve from the first box to the last, performing the convolutional operating on every 64x64 matrix. On the other hand, the Pooling Layer purposes to decrease the computational power by doing the dimensional reduction. It provides the maximum value within the covered image by the Kernel. In our model, we have 2 Pooling layers after each convolutional layer, what happens is it selects the maximum element from the region of the feature map covered by our 2x2 filter. Thus, the output after the max-pooling layer would be a feature map containing the most prominent features of the previous feature map. Fully Connected Layer (FC Layer) flats the output image into a form of a column vector after converting the image output to a specific form (LeCun et al, 2015). FC Layer of the first model consists of 3 hidden layers with 260 hidden units in each layer and 2 output nodes which has the Softmax Activation function. FC Layer of the second model consists of 3 hidden layers with 260 hidden units in each layer and 1 output node which has the Sigmoid Activation function. The output of our pooling layer will be the input of the FC Layer which is flattened and then fed into the fully connected layer. For each layer of the Artificial Neural Network, the following calculation takes place $g(Wx + b)$ where x is the input vector, W is the weight matrix, b is the bias vector and g is the activation function which is ReLU in all hidden layers in both models. This calculation is repeated for each layer. After passing through the fully connected layers, the final layer uses the Sigmoid Activation function in the first model and the Softmax Activation function in the second model. And so finally, we have the probabilities of the object in the image belonging to the different classes.

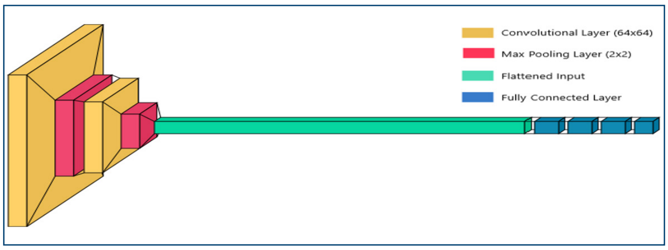

Figure 3. General Structure of the CNN.

Results and Discussion

This section provides the performance results of the convolutional neural network (CNN) model using sigmoid and softmax activation functions and subsequently discusses the training, validation, and testing accuracies. **Table 1** presents the performance results of the convolutional neural network in detecting dry and wet potholes.

Evaluation Metrics

The following evaluation metrics were used in the evaluation of the created CNN (Yacouby & Axman, 2020). The accuracy score is used as an evaluation metric in this study.

$$Accuracy \quad (TN + TP) / (TN + TP + FN + FP)$$

where TP is the True Positive, TN is the True Negative, FP is the False Positive, and FN is the False Negative.

Training, Validation, and Test Accuracies

As shown in Table 1, our model using the Sigmoid activation function in the output layer has 91%, 96% and 83% accuracy scores over datasets 1,2 and 3 respectively. Another model using the Softmax activation function in the output layer has 81%, 96% and 85% accuracy scores over datasets 1,2 and 3 respectively. Based on these results, it can be said that the Sigmoid activation function was more effective in detecting the potholes images than the Softmax activation function.

Table 1. Evaluation scores of the employed CNN based on three different datasets

Activation Function	Dataset	Training Accuracy (%)	Test Accuracy (%)	Validation Accuracy (%)
Sigmoid	Dataset 1	95	91	83
	Dataset 2	99	96	78
	Dataset 3	95	83	87
Softmax	Dataset 1	92	81	82
	Dataset 2	96	96	90
	Dataset 3	94	85	87

The sigmoid function achieved the highest training accuracy rate (99%) on dataset 2. The softmax activation function provided the highest training accuracy (96%) which is less than the accuracy given by the sigmoid activation function on dataset 2. On the other hand, the best validation accuracy is achieved by the softmax activation function and the least validation accuracy is given by the sigmoid function on dataset 2. These results highlighted the importance of choosing a proper activation function to solve cognitive tasks in convolutional neural network applications.

Robustness of the used CNN

The test accuracy rates of the CNN in the use of Sigmoid activation function on datasets 1,2 and 3 range from 83% to 96%. On the other hand, the accuracy rates of the CNN that have been created with Softmax activation function on datasets 1,2 and 3 range from 81% to 96%. The difference between the test accuracy rates of CNN (with Sigmoid activation function) is 13% while the difference between the test accuracy rates of CNN (with Softmax activation function) is 15%. It can be inferred from the rates, CNN (with Sigmoid activation function) algorithm can be considered more robust than the CNN (with Softmax activation function).

DISCUSSION

The results of this study demonstrate the effectiveness of using convolutional neural networks (CNN) with both Sigmoid and Softmax activation functions for detecting dry and wet potholes. The CNN algorithm created using the Sigmoid activation function outperformed the Softmax algorithm in detecting potholes across all three datasets, achieving the best statistical scores. These findings suggest that the Sigmoid activation function is more effective for pothole detection than the Softmax activation function. Furthermore, the CNN algorithm that employed the Sigmoid activation function was found to be more robust than the Softmax algorithm, with a difference in test accuracy rate of only 2%. These results highlight the potential of deep learning methods to improve pothole detection and road safety. Additionally, the proposed pothole detection model achieved to provide robust scores based on the presented test scores in Table 1.

Study Limitations

While this study shows promising results for using CNN algorithms in pothole detection, there are some limitations to consider. First, the study only used three datasets, and further validation using larger and more diverse datasets is necessary. Additionally, the study only focused on the performance of the CNN algorithms with Sigmoid and Softmax activation functions, and other deep learning techniques may be worth exploring to improve accuracy scores.

CONCLUSION

This study suggests that the use of CNN algorithms with the Sigmoid activation function is more effective for detecting dry and wet potholes compared to the Softmax activation function. The CNN algorithm created using the Sigmoid activation function provided the best statistical scores across all three datasets and was found to be more robust than the Softmax algorithm. While there are limitations to the study, the results demonstrate the potential of using deep learning techniques for improving pothole detection and road safety. As a next step, a hybrid deep learning approach could be proposed to further improve the accuracy score of the CNN algorithm with the Sigmoid activation function.

ETHICAL DECLARATIONS

Referee Evaluation Process: Externally peer-reviewed.

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Author Contributions: All of the authors declare that they have all participated in the design, execution, and analysis of the paper, and that they have approved the final version.

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Qusai Gazawy

Qusai Gazawy is a 4th grade student at Cankiri Karatekin University with a passion for Game Development and Machine Learning. He is also a remote Python tutor at Kodland, where he shares his skills and knowledge to help others develop their programming and data analysis skills.

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Prediction of heart attack risk using linear discriminant analysis methods

Esra Sivari, Selim Sürücü

Department of Computer Engineering, Çankırı Karatekin University, Çankırı, Turkey

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Corresponding Author: Esra Sivari, esrasivari@karatekin.edu.tr

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ABSTRACT

Aims: A heart attack is when blood flow to the heart muscle is interrupted. During a heart attack, the risk of permanent damage to the heart increases with every second that the heart tissue is not supplied with enough blood. If early and appropriate intervention is not carried out, the heart starts to fail and dies. The main risk factors for heart attack are smoking, cholesterol, diabetes, high blood pressure, age, obesity, genetics and high levels of certain substances produced in the liver. This study aims to use machine learning methods to predict the risk of heart attack using a dataset created by taking into account risk factors.

Methods: The performance of three types of linear discriminant analysis classifiers - Normal, Ledoit-Wolf and Oracle Shrinkage Approximating - was compared on the Cleveland data set.

Results: Normal linear discriminant analysis gave the best classification with an accuracy of 83.60% and performed better than regularised versions.

Conclusion: Linear discriminant analysis is a promising classifier for predicting myocardial infarction. It can be used in hospitals as an objective and automated system that reduces the workload of specialists and helps to reduce diagnostic costs.

Keywords: Machine learning, heart attack risk, linear discriminant analysis

INTRODUCTION

The heart is a vital organ located on the left side of the muscular chest and pumps almost 8000 litres of blood into the circulation, contracting on average 100,000 times a day. Cardiovascular diseases such as valvular disease, myocardial disease and myocardial infarction, which are related to the coronary arteries that supply blood to the heart tissue, can result from any disorder in the heart's structure. The WHO estimates that cardiovascular disease is the leading cause of death worldwide, accounting for 17.9 million deaths annually, and WHO research suggests that this number will rise to around 30 million by 2040. One third of deaths occur prematurely in middle-aged people, while four out of five deaths from cardiovascular disease are due to heart attacks and strokes.(Virani et al., 2021).

A heart attack is when the blood supply to the heart muscle is interrupted by blockage or narrowing of the coronary arteries, which are responsible for supplying the heart with oxygen and nutrients. During a heart attack, the risk of permanent damage increases with every second that the heart tissue is deprived of blood. Any sudden blockage in the arteries that supply blood to the heart can cause the heart muscle to be starved of oxygen, resulting in damage to the heart tissue. Loss of heart tissue occurs if the vessel is not opened early and with the correct procedure. The loss reduces the heart's ability to pump and heart failure occurs. Causes such as smoking, cholesterol, diabetes, high blood pressure, age, obesity, genetics and elevated levels of certain substances produced in the liver are the main risk factors for heart attack. By taking these factors into account, the risk of heart attack can be predicted and people can be aware and take early precautions.

Today, prediction and classification applications are being developed for the early diagnosis of many diseases, thanks to machine learning techniques applied to medical data. These applications offer the benefits of objectivity in diagnosis and high and fast performance, reducing the workload and cost of the specialist. Machine learning studies conducted to predict whether an individual is at risk of a heart attack have focused on a 13-character Cleveland dataset (Detrano, 1989). In previous studies, many have proposed support vector machines (SVM) (Xing et al., 2008), neural networks (Ajam, 2015), decision trees (Thenmozhi& Deepika, 2014), K-Nearest Neighbour (KNN) (Wettschereck&Dietterich, 1995) and naive Bayes (Srinivas et al., 2010) methods to classify the Cleveland dataset and estimate the risk of heart attack for individuals, and experimental results have shown satisfactory accuracy. Another frequently used technique is the combination of Principal Component Analysis (PCA), one of the feature selection and size reduction methods, with machine learning algorithms (Aec et al., 2013).Fuzzy logic (Guidi et al., 2014), ensemble learning (Das et al., 2009) and deep learning (Manimurugan et al., 20-22) are recommended methods.

Looking at the studies conducted in recent years to classify the Cleveland dataset, machine learning algorithms based on statistical methods are recommended to achieve high performance. Ensemble techniques, such as Latha and Jeeva (2019) bagging and amplification in heart disease risk determination, provided a maximum accuracy increase of 7% in improving the predictive accuracy of weak classifiers. Bharti et al. (2021) achieved 94.2% accuracy with a hybrid method that included machine learning and deep learning algorithms. Santhanam and Ephzibah (2013) proposed the PCA technique for feature selection and achieved classification accuracies of 92 and 95.2% with combinations of PCA + regression and PCA + ANN. Dissanayake and Johar (2021) compared different feature selection algorithms (ANOVA, chi-square, mutual information, ReliefF, forward feature selection, backward feature selection, exhaustive feature selection, recursive feature elimination, lasso regression and ridge regression) on the dataset and the backward feature selection technique achieved the highest classification accuracy of 88.52%. Gárate-Escamila et al. (2020) achieved 98.7% accuracy on the Cleveland dataset using Chi-square and Principal Component Analysis (CHI-PCA) with Random Forests (RF). Katarya and Meena (2021) compared the performance of nine different machine learning classifiers and reported 95.60% accuracy with Random Forest.

For the detection of coronary artery disease, Singh et al. (2018) proposed the Fisher method and generalised discriminant analysis with binary classifiers for feature selection. Negi et al. (2016) used PCA independent linear discriminant analysis to study the electrocardiogram. Asl et al. (2008) proposed the combination of generalised discriminant analysis and SVM for arrhythmia classification.

However, to our knowledge, discriminant analysis has not been used in previous studies of the Cleveland data set. In this study, linear discriminant analysis techniques are proposed to predict the risk of myocardial infarction. The performances of three types of linear discriminant analysis classifiers, Normal, Ledoit-Wolf and Oracle Shrinkage Approximating (OAS), were compared on the Cleveland dataset. The main contribution of this study is that it is the first study to propose LDA algorithms for classification of the Cleveland dataset. Another contribution is the estimation of the risk of myocardial infarction with high performance without using feature selection algorithms with LDA algorithms.

METHODS

A Cleveland dataset consisting of 303 samples with 13 features was used for the application. The number of patients at risk of heart attack in the dataset is 165. The features and explanations of the dataset are given in Table 1. As the dataset did not contain any null values, the data was directly applied to the machine learning algorithms without the feature selection process. The method overview scheme is shown in Figure 1. The data was randomly divided into training and test sets, of which 61 were test data. With the 10-fold cross-validation technique, the training and validation phases were performed simultaneously. The training phase was carried out using Normal, Ledoit-Wolf and OAS LDA algorithms with Least Squares Optimisation (lsqr). After the training phase, the selected performance metrics and the classes of the test data were estimated and their performances were compared.

Table 1. The features and descriptions of theCleveland dataset

Feature Names	Features Descriptions
Age	Age of the patient
Sex	Sex of the patient (1=male; 0=female)
exang	Exercise induced angina (1=yes; 0=no)
ca	Number of major vessels (0-3)
cp	Chest Pain type chest pain type (1=typical angina; 2=atypical angina; 3=non-anginal pain; 4=asymptomatic)
trtbps	Resting blood pressure (in mm Hg)
chol	Cholestoral in mg/dl fetched via BMI sensor
fbs	Fasting blood sugar > 120 mg/dl (1=true; 0=false)
rest_ecg	Resting electrocardiographic results (0=normal; 1=having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV); 2=showing probable or definite left ventricular hypertrophy by Estes' criteria)
thalach	Maximum heart rate achieved
target	0= Less chance of heart attack 1= More chance of heart attack

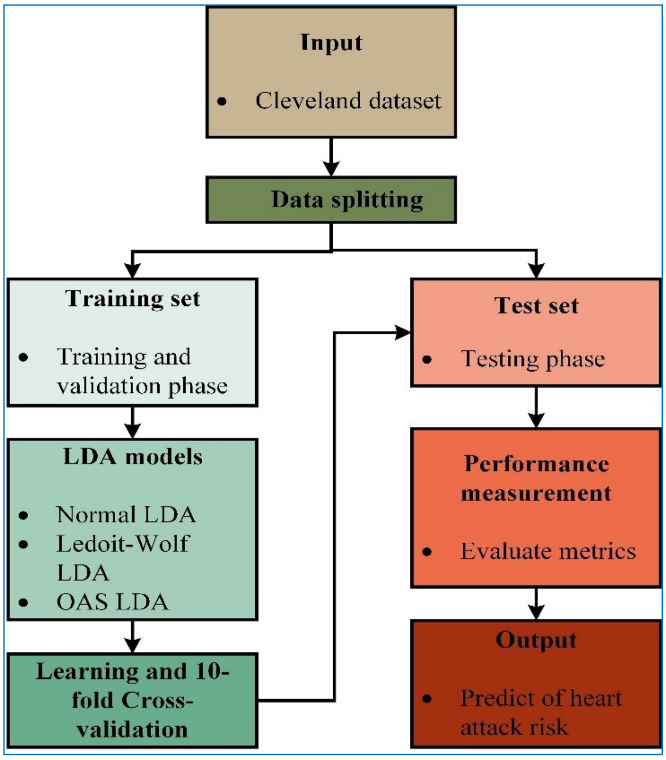

Figure 1. Overview of the method.

Linear discriminant analysis (LDA) is a machine learning technique used for classification, dimension reduction and feature extraction in pattern classification problems. Ronald A. Fisher developed the original linear discriminator in 1936 as a two-class technique (Izenman, 2013). As a supervised classification method, LDA makes a class prediction with a linear decision surface created by fitting conditional class densities to the data and using Bayes' rule (Equation (1)). In a case where there are two classes, i and j, Pji in equation (1) is the base probability (prior probability) of each class observed in the training data, and fi (x) is the estimated probability of x for class i.Linear discriminant analysis (LDA) is a machine learning technique used for classification, dimension reduction, and feature extraction in pattern classification problems. Ronald A. Fisher developed the original linear discriminant in 1936 as a two-class technique (Izenman, 2013). As a supervised classification method, LDA makes a class prediction with a linear decision surface created by fitting conditional class densities to the data and using Bayes' rule (Equation (1)). If there are two classes, i and j, P_{ji} in Equation (1) is the base probability (prior probability) of each class observed in the training data, and $f_i(x)$ is the estimated probability of x for class i. If there are two classes, i and j, P_{ji} is the base probability (prior probability) of each class observed in the training data.

$$P(y=i|x) = \frac{P(x|y=i)P(y=i)}{\sum j \sum P_{ji} * f_i(x)} \quad (1)$$

The discriminant rule uses the probability of each class and the probability of the data belonging to each class. When the Gaussian distribution function is applied to the data, the distribution of x is characterised by its mean (μ) and covariance (Σ), and the discriminant function given in Equation (2) is obtained.

$$D_i(x) = log f_i(x) + log P_{ji} \quad (2)$$

The discriminant function calculates the probabilities of how much data x belongs to each class. The decision surface separating classes i and j is the set x, where the two discriminant functions for the two classes have the same value, and any data falling on the decision surface belongs equally to both classes (undefined). LDA occurs when we assume equal covariance between classes i and j; all classes have the same covariance matrix. The equal covariance discriminant function of LDA is given in Equation (3). The mean, covariance and prior probability given in Equation (3) are estimated from the training data, and the probability of the class with the largest value determines the output estimate.

$$D_i(x) = x^T \mu_i \Sigma^{-1} - \frac{1}{2}\mu_i^T \mu_i \Sigma^{-1} + log P_{ji} \quad (3)$$

Shrinkage is a penalty term, similar to applying L1 or L2 regularisation to the optimiser, to prevent overfitting in the LDA algorithm. When shrinkage is used as an estimator, a better variance estimator can be obtained than the original raw estimate. The gamma function is added to the estimator to obtain shrinkage. Gamma functions are any function that gives a shrinkage effect. The Ledoit-Wolf estimator (Ledoit& Wolf, 2004) is the most widely used shrinkage algorithm for regularising covariance matrices and improving their stability. The Ledoit-Wolf estimator asymptotically calculates the optimal shrinkage parameter by minimising a Mean Squared Error (MSE) criterion function. The Oracle Shrinkage Approximating (OAS) estimator (Chen et al., 2010) is another shrinkage algorithm that estimates the covariance matrix by iteratively approximating the shrinkage parameter.

RESULT

Learning curves are used to evaluate the results of the training and validation phases. Overfitting or underfitting situations can be observed in a learning curve graph by looking at the generalisation gap between the training and validation curves. A small generalisation gap is normal for an efficient training phase, because the training data is more than the validation data. Figure 2 shows the learning curves of the Normal, Ledoit-Wolf and OAS LDA classifiers. Ten points in the learning curves show cross-validation accuracy values according to the number of training data. The curves show that there is no overfitting or underfitting during the training phase. However, as the number of training samples is increased, it is observed that the generalisation ability increases and the training and validation accuracy scores increase. According to the shading around the curves showing the standard deviation values, the training standard deviation is low and the validation standard deviation is high.

During the test phase, 61 examples were used, including 31 patients at low risk of myocardial infarction and 30 at risk of myocardial infarction. The confusion matrix gives the true positive (TP), false negative (FN), true negative (TN) and false positive (FP) values used to calculate the performance metrics. Figure 3 shows the confusion matrices of the LDA classifications. The Normal LDA made the highest prediction with 51 correct and 10 incorrect predictions. The OAS LDA made the lowest prediction with 44 correct and 17 incorrect predictions. Normal LDA and Ledoit-Wolf LDA made the same number of incorrect predictions from both classes, while OAS LDA made the same number of correct predictions from both classes. These equations result in performance metrics that are equal or very close to each other.

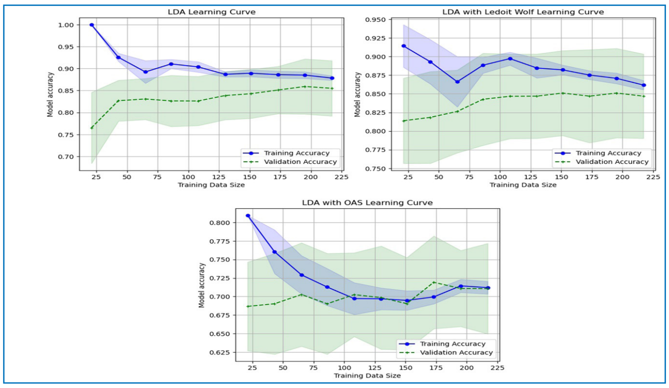

Figure 2. Learning curves of the LDA classifiers.

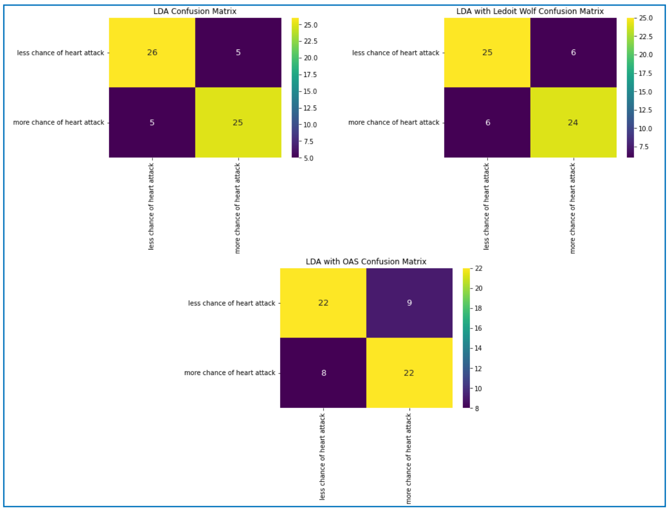

Figure 3. Confusion matrices of the LDA classifiers.

The performance measures and mathematical formulae used to calculate the test results are given in Table 2. Accuracy (ACC) is the ratio of correct predictions to all predictions. Precision is the ratio of true positives to all positives. Recall measures how accurately the true positives were predicted. The F_1 score is the harmonic mean of precision and recall. The area under the ROC curve (AUC) value measures how well two classes can be discriminated, and a value of 1 is desired for perfect discrimination. The F_1 and ACC metrics are positive class dependent, but the Matthews Correlation Coefficient (MCC) gives positive and negative class dependent results.

Table 2.Mathematical formulas of the performance metrics

Performance Metrics	Mathematical Formulas
Accuracy (ACC)	$$\frac{TP+TN}{TP+FP+FN+TN} \quad (4)$$
Precision	$$\frac{TP}{TP+FP} \quad (5)$$
Recall	$$\frac{TP}{TP+FN} \quad (6)$$
F_1 Score	$$2\,X\,\frac{Precision X Recall}{Precision+Recall} \quad (7)$$
Matthews Correlation Coefficient (MCC)	$$\frac{TP\times TN-FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (8)$$

Normal LDA gave the best classification with 83.60% ACC and 67.20% MCC. Ledoit-Wolf LDA was the second best with 80.32% ACC and 60.64% MCC. The OAS LDA performed poorly with 72.13% ACC and 44.30% MCC. The balance of the test set and the number of correct and incorrect predictions ensured that the ACC and AUC metrics had the same values, and the Precision, Recall and F_1 metrics had the same values. The F_1 values for Normal, Ledoit-Wolf and OAS LDA are 83.33%, 80% and 72.12% respectively. In medical applications, the precision metric must be higher than the recall. While the recall (73.33%) of OAS LDA is higher than the precision (70.96%), it is the same for the other LDA classifiers (Normal LDA: 83.33%, Ledoit-Wolf LDA: 80%).

Table 3. Test results of the LDA classifiers

Algorithm	ACC (%)	Precision (%)	Recall (%)	F_1 Score (%)	AUC (%)	MCC (%)
Normal LDA	83.60	83.33	83.33	83.33	83.60	67.20
Ledoit-Wolf LDA	80.32	80.00	80.00	80.00	80.32	60.64
OAS LDA	72.13	70.96	73.33	72.12	72.15	44.30

DISCUSSION

LDA and its variants have been frequently proposed in the classification of various cancers using DNA microarray data. Dudoit et al (2011) classified two-class leukaemia DNA microarray data using Diagonal Linear Discriminant Analysis (DLDA) and Fisher Linear Discriminant Analysis (FLDA) methods. The authors reported the number of misclassified tumour samples as 0 for DLDA and 3 for FLDA. Li et al (2005) proposed Generalised Linear Discriminant Analysis (GLDA) for the detection of seven different cancer types using DNA microarray data. The average classification error rate for lymphoma was 0.05. Sharma and Paliwal (2008) misclassified only 2 samples in the three-class lung adenocarcinoma dataset using the gradient LDA method. A study by Huang et al (2009) compared LDA methods for cancer classification based on gene expression data and reported that the mean test error of LDA modification methods was lower than that of the LDA method. These studies suggest that promising results can be obtained by applying LDA and its variants to various health data.

LDA is a supervised classification technique that is considered part of building competitive machine learning models, and its simplicity of implementation is an advantage. However, LDA can fail in some cases where the mean of the data distributions is shared and cannot create a new axis that makes both classes linearly separable. Linear decision boundaries may not sufficiently separate classes, and a regularised version of LDA or non-linear discriminant analysis can be used for more general boundaries.

For this application, Normal LDA outperformed the regularised versions. This result shows that linear separation may be more appropriate for the Cleveland dataset, but the overall classification performance is lower than studies in the literature. The reason for the poor performance is that no preprocessing or feature selection methods are applied to the data beyond the capabilities of the LDA classifier. The studies in the literature were pre-processed, and in this study the raw data was used in the classification of selected features. Considering the performance under these conditions, the LDA algorithm is very promising for the problem of measuring heart attack risk.

CONCLUSION

In this study, Normal LDA and the regularised versions Ledoit-Wolf and OAS LDA algorithms were used to automatically and objectively estimate the risk of myocardial infarction. According to the experimental studies on the Cleveland dataset, Normal LDA classified the raw data with 83.60% ACC. Raw data classification without data pre-processing and feature selection methods greatly affected the inability of the performance metrics to achieve high values. Suppose that experimental studies are developed by combining the proposed LDA algorithms with data pre-processing and feature selection methods. In this case, the applicability of this application in hospitals as an objective and automatic system to help experts reduce workload and costs can be suggested. In the future, such applications could be used to create mobile applications or devices that predict the risk of heart attack, independent of the specialist.

ETHICAL DECLARATIONS

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Esra Sivari

Esra Sivari received the B.S. degree in computer engineering from Selcuk University, Turkey, in 2017, and the M.S. degree in electrical and electronics engineering from Cankiri Karatekin University, Turkey, in 2021. She is currently a Ph.D. student at Ankara University Computer Engineering and a research assistant at Cankiri Karatekin University Computer Engineering. Her work focuses on the field of artificial intelligence in medicine.

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Investigation of financial applications with blockchain technology

Muhammed Ali Muhammed

Department of Electronic and Computer Engineering, Faculty of Engineering, Çankırı University, Çankırı, Türkiye

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Corresponding Author: Mohammed Ali Mohammed, Lm9997621@gmail.com

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ABSTRACT

The advent of blockchain technology and the rise of cryptocurrencies have had a profound impact on the financial industry and beyond. This article explores the recent advancements in machine learning (ML) and blockchain technology for the prediction of cryptocurrency prices. Our study presents a ML system that utilizes six different cryptocurrency datasets and applies various ML techniques such as LSTM, CNN, SVM, KNN, XGBoost, Astro ML, LASSO, RIDGE, linear regression, DT, and GP to predict prices. The research found that complex models may not always perform better than simpler models, and our proposed model had better performance as evaluated by the RMSE. The research evaluated various machine learning techniques for predicting cryptocurrency prices and reported the following RMSE values: Bitcoin prediction using Nadaraya-Watson kernel regression yielded an RMSE of 0.17, while Dogecoin prediction with linear regression resulted in an RMSE of 0.032. Ethereum price prediction using Gaussian regression achieved an RMSE of 0.02. For USD Coin, a combination of XGBoost, Gaussian regression, and Ridge techniques led to an RMSE of 0.014. Binance Coin price prediction using Gaussian regression had an RMSE of 0.032, and finally, Cardano Coin prediction employing LSTM reached an RMSE of 0.059.

This study demonstrated the effectiveness of various machine learning techniques in predicting cryptocurrency prices. The research contributes valuable insights to the field and can guide future work in cryptocurrency price prediction. The proposed model achieved promising results as evaluated by the RMSE metric.

Keywords: Blockchain, Cryptocurrency, Machine Learning.

INTRODUCTION

Over the past decade, the global economy and payment methods have undergone a significant transformation, primarily due to the emergence of digital currencies facilitated by advancements in information technology (IT). These digital currencies, such as Bitcoin and Ethereum, have gained popularity because of their potential for gains and expanding user base, and they are supported by blockchain technology. Blockchain enables decentralized digital currencies that offer increased autonomy, but this also creates significant challenges for governments and financial institutions (Gowda & Chakravorty, 2021). Bitcoin and Ethereum are currently the most widely used cryptocurrencies, with large trading volumes and market capitalizations. For instance, in April 2021, Bitcoin had a market capitalization of USD 1,304 billion and a trading volume of USD 64 billion, while Ethereum's market capitalization was USD 265 billion with a trading volume of USD 38 billion (Kim et al., 2021a). To manage potential risks for investors, academic researchers are currently examining the future value of cryptocurrencies and the market.

In spite of the difficulties encountered, ML and blockchain technologies have made remarkable strides in recent years, leading to the creation of novel and better products utilized by billions of people globally. The primary focus of researchers has been on implementing these methods in financial markets, including the forecasting of stock market trends and the detection of manipulation, which also have implications for cryptocurrencies as financial assets. In comparison to other fields, blockchain and ML research are comparatively young and less advanced, with more emphasis placed on non-technical aspects of Blockchain technology. Nevertheless, the rapid advancement of ML and the novelty of Blockchain technology provide an opportunity for future research and development in this field.

Literature Review

This related work covers various studies and experiments related to Bitcoin. (Gundlach et al., 2021) examined the correlation between the memory pool's availability and the dispersion of Bitcoin transaction confirmation times. (Koops, 2018) studied the probability distribution of the time it takes for Bitcoin transactions to be confirmed and developed stochastic fluid queueing algorithms to represent it. (Pabuçcu et al., 2020) utilized ML methods to forecast fluctuations in Bitcoin prices. (Rahouti et al., 2018) investigated the main security issues in the Bitcoin protocol, while (Hitam & Ismail, 2018) compared various ML algorithms for Bitcoin forecasting. (Ho et al., 2021)developed ANN models and ML algorithms to forecast the value of Bitcoin (Jagannath et al., 2021) presented a self-adaptive approach based on the jSO optimization algorithm to accurately predict the value of Bitcoin. (Yogeshwaran et al., 2019) explained how a trained machine model can predict the price of a cryptocurrency given enough information and computing power.

Our article seeks to determine the most accurate pricing prediction algorithm for selected cryptocurrencies. To achieve this, we plan to utilize several ML techniques, including linear regression, LASSO, decision tree, Ridge and XGboost, SVM, KNN, Kernel regression, CNN, and LSTM. The extensive literature on predicting cryptocurrency prices supports our research direction.

METHODS

Our model is a ML based system that utilizes six different cryptocurrency datasets for its operation. The first step in building the model is preprocessing of the data, which involves normalizing the data to make it suitable for the ML algorithms. After preprocessing, various ML techniques are applied to the data to create the final model. These techniques include LSTM, CNN, SVM, KNN, XGBoost, Astro ML, LASSO, RIDGE, linear regression, DT, and GP. The choice of technique is determined by the specific problem being solved and the characteristics of the data. The goal of this model is to predict prices of the cryptocurrency.

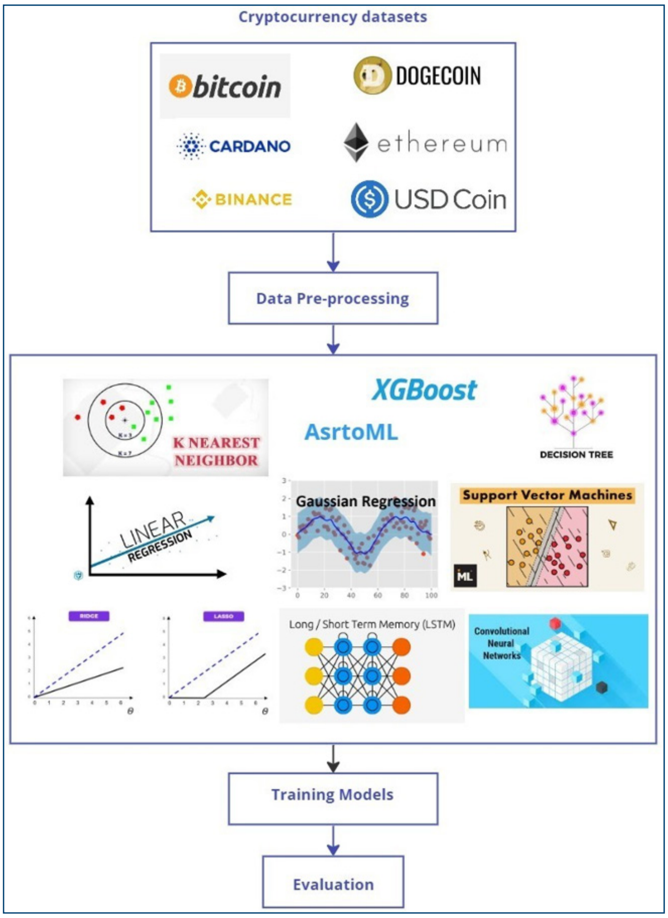

Figure 1. The methodology process

Cryptocurrency Datasets

Cryptocurrency datasets contain information about the various cryptocurrencies. The dataset contains 11 types of cryptocurrencies in USD and includes the prices of each type for the past 6 years.

In this study, we used six type cryptocurrencies datasets based on their availability of historic price data. These cryprocurrencies are Bitcoin, Dogecoin, Ethereum, USDCoin, Binance, and Cardano. **Table 1** lists the trade symbols for these cryptocurrencies.

Table 1: Symbol list of Cryptocurrencies datasets

Cryptocurrency	Symbole
Bitcoin	BTC
Dogecoin	D
Ethereum	ETH
USDCoin	USDC
Binance Coin	BNB
Cardano Coin	ADA

The dataset of this study was obtained from Dropbox. To read the dataset we use Pandas framework for Python programming language. These dataset converts a comma-separated values file into a DataFrame, which is a tabular structure that can handle different types of data and allows for iteration or chunking of the file. It contain seven features present as follows:

- date: represents the calendar day, month, and year of cryptocurrency prices.
- open: refers to the initial price at the start of the day.
- high: refers to the highest price reached during the day.
- low: refers to the lowest price reached during the day.
- close: refers to the final price at the end of the day.
- adj_close: refers to the average price of the day.
- volume: refers to the amount of cryptocurrency traded during the day

Data preprocessing is the process of preparing data for analysis and modeling. It involves a series of steps to clean, transform, and format the data so that it can be effectively used by ML algorithms. Some common steps in data preprocessing include, Data cleaning, Data transformation, Data formatting, and data reduction. In this paper, we use only data cleaning and data transformation. Then, the dataset was split into training (70%) and testing (30%) sets. We identified eleven models that are commonly used for prediction price. Each model has been built from scratch for each cryptocurrency. In order to enable a comparison between our models, we used the same model parameters across different cryptocurrency. In the following sections, we will discuss each model individually.

Predictive Methods

In the study, the dataset was divided into a training set and a testing set, with 70% and 30% of the data, respectively. The aim of the study was to predict cryptocurrency prices using eleven commonly used models. Each model was developed separately for each cryptocurrency, but the same parameters were used for each model to facilitate comparison between them. The study will discuss each model individually in subsequent sections.

Long Short-Term Memory Architecture

LSTM (Lahmiri & Bekiros, 2019) models are popular for cryptocurrency price prediction because they can memorize previous inputs and identify long-term dependencies in time series data. These models are trained on historical price data and other relevant variables to make predictions on future prices (Hu et al., 2015) The architecture of the LSTM model involves an input layer for historical price data and other variables, an LSTM layer to process the input data and learn dependencies, and an output layer to produce future price predictions. A loss function is used to evaluate the model's performance, and an optimization algorithm updates the model parameters to minimize the loss function. By following these steps, LSTM models can effectively predict cryptocurrency prices.

Convolutional Neural Network Architecture

A CNN (Hu et al., 2015) can be used to analyze cryptocurrency data to make informed trading decisions, as it is well-suited for image and time-series data. A CNN for cryptocurrency price prediction typically consists of an input layer for historical price data and relevant variables, convolutional layers to extract features and detect patterns, pooling layers to down-sample the output, fully connected layers to make predictions based on the features, and an output layer to produce the final prediction of the cryptocurrency price. The input data is preprocessed and normalized before being fed into the model.

Support Vector Machines Architecture

SVMs (Noble, 2006) use historical price data to predict future price movements by finding the best function that fits the data and predicts continuous values. This is done by transforming the data into a high-dimensional feature space, where a hyperplane can represent the prediction function. The optimization problem seeks to minimize the error between predicted and actual values while maximizing the margin, which is the distance between the hyperplane and the closest data points. This ensures a robust prediction function that is not overfit to the training data. To make predictions on new data, the new point is transformed into the feature space and plugged into the prediction function. The output of the function is the predicted value for the new data point.

K-nearest Neighbors Architecture

K-Nearest Neighbors (KNN) (Peterson, 2009) is a simple ML algorithm that can be used for cryptocurrency price prediction. It stores all available data points and corresponding continuous target values. When a new data point is encountered, the algorithm finds the K nearest neighbors based on a distance metric, and uses their target values to predict the new data point. The prediction is calculated as the average of the target values of the K nearest neighbors. While KNN regression is fast and simple, it can be sensitive to the choice of distance metric and number of neighbors used, and may not perform well for high-dimensional data. Careful parameter selection is necessary for good results.

XGBoost Architecture

XGBoost (Chen & Guestrin, 2016) is a ML algorithm that uses a series of weak models, such as decision trees, to improve prediction accuracy. It uses gradient descent to optimize the parameters of the models and iteratively improve their performance. The tree building process involves initializing residuals, splitting the data into subsets based on feature values, and selecting the split that results in the minimum loss. Tree pruning is used to remove branches that do not significantly contribute to prediction accuracy. Boosting is used to combine the predictions from multiple trees, with each tree being weighted based on its accuracy. The final prediction is obtained by summing the weighted predictions from all the trees, resulting in a more accurate overall prediction.

Astro ML Architecture

AstroML (VanderPlas et al., 2012) is a Python library designed for ML applications in astrophysics that can also be applied to cryptocurrency data. In this context, regression techniques from AstroML can be utilized to model the relationship between various features and the price of a cryptocurrency. The choice of regression model depends on factors such as the complexity of the data, the nature of the relationship between features and the target variable, and the desired level of accuracy. Regression techniques such as linear regression, polynomial regression, decision trees, and RF can be employed to make predictions about the future price of a cryptocurrency based on its past performance and other relevant factors.

LASSO Architecture

Lasso (Park & Casella, 2008) is a ML technique used to model the relationship between features and the price of a cryptocurrency. Its goal is to improve the interpretability and accuracy of the model by adding a penalty term to the loss function during optimization. This encourages the model to have sparse coefficients, reducing the importance of many features and resulting in a more parsimonious and interpretable model. Lasso regression selects a subset of relevant features to use in the prediction, making it easier to understand the relationship between the features and the target variable and potentially leading to more accurate predictions.

RIDGE Architecture

Ridge Regression (Hoerl & Kennard, 1970) is a regularization method used in regression analysis to model the relationship between features and the target variable, such as the price of a cryptocurrency. Its main goal is to improve the stability and interpretability of the model by adding a penalty term to the loss function that encourages smaller coefficients for all features.

The Ridge method achieves this by reducing the magnitude of the coefficients, making the model less sensitive to small variations in the data, resulting in a more stable and interpretable model. As a result, Ridge Regression can be useful for avoiding overfitting, reducing multicollinearity, and improving the accuracy of predictions by creating a more stable and interpretable model

Linear Regression Architecture

Linear Regression (LR) (Weisberg, 2005) is a statistical method used to model the relationship between a dependent variable and one or more independent variables. This method can be applied in the context of cryptocurrency to model the relationship between various features and the price of a cryptocurrency. The LR model assumes that the relationship between the dependent variable and independent variables can be modeled as a linear equation. The model estimates the coefficients for each feature by using historical data for each feature and the cryptocurrency price. The coefficients are then used to predict the future price of a cryptocurrency by multiplying the values of the independent variables by their corresponding coefficients and summing the results.

Decision Tree Architecture

A DT (Quinlan, 1986) algorithm is a ML tool that uses a tree-like structure to weigh the costs, probabilities, and benefits of different potential outcomes. Starting with a single node, the algorithm branches into possible outcomes, with each leading to additional nodes that branch off into other possibilities. Decision tree algorithms provide a systematic and mathematical approach to predicting the best choice by mapping out potential outcomes and the factors that influence them. These algorithms can be used for various purposes, from informal discussions to automating complex decision-making processes.

Gaussian Process Architecture

A Gaussian Process (GP) (Quiñonero et al., 2005) for cryptocurrency prediction models the relationship between predictors and the cryptocurrency price as a Gaussian distribution. This enables probabilistic predictions and quantification of uncertainty. A Gaussian prior distribution is assigned to the unknown function that maps predictors to the cryptocurrency price, and it is updated to a posterior distribution using observed data. The posterior distribution reflects the observed relationships and can be used to make predictions and estimate their uncertainty.

RESULTS

The article discusses the evaluation of different models for predicting cryptocurrency prices using RMSE values. XGBoost is the best performer with the lowest RMSE values for most cryptocurrencies. Ridge and GR models also demonstrate relatively low RMSE values and are good performers. However, other factors such as data availability, computational efficiency, and specific application need to be considered while selecting the best model.

The article discusses the evaluation of different models for predicting cryptocurrency prices. The performance of these models is evaluated using RMSE values. Lower RMSE values indicate better predictive accuracy of the model.

The XGBoost model is the best performer with the lowest RMSE values for most cryptocurrencies. For instance, its RMSE value of 0.014 for USD Coin is the lowest among all models. The Ridge and GR models also demonstrate relatively low RMSE values for most cryptocurrencies, indicating that they have good predictive accuracy as well.

Table 2:RMSE values of different models for predicting cryptocurrency prices

Model	Bitcoin	Dogecoin	Etherum	USD coin	Binance	Cardano coin
CNN	0.68	0.90	0.78	0.59	0.75	0.75
SVM	0.35	0.22	0.26	0.03	0.39	0.35
KNN	0.31	0.22	0.21	0.015	0.38	0.31
XGBoost	0.07	0.21	0.17	0.014	0.37	0.19
LASSO	0.42	0.22	0.33	0.032	0.39	0.36
Ridge	0.03	0.19	0.03	0.014	0.15	0.049
LR	0.02	0.03	0.02	0.015	0.032	0.03
Kernel regression	0.17	0.23	0.33	0.024	0.4	0.3
DT	0.32	0.22	0.2	0.02	0.37	0.22
GR	0.02	0.03	0.02	0.014	0.032	0.03
LSTM	0.26	0.22	0.08	0.01	0.25	0.059

However, other factors such as data availability, computational efficiency, and specific application need to be considered while selecting the best model. Therefore, based on the RMSE values provided in the table, the XGBoost and Ridge models seem to have better predictive accuracy than the other models.

The passage compares the RMSE results of various authors who applied different techniques to predict the price of different cryptocurrencies. Pabuçcu et al. experimented with various methods and found that the Random Forest (RF) technique had the best RMSE of 0.293, followed by ANN with 0.341, SVM with 0.438, and Naive Bayes with 0.461. Meanwhile, Jagannath et al. utilized LSTM to forecast the price of Bitcoin, but their RMSE of 1.9 was relatively higher than the other models. Awoke et al. improved on this method by applying both LSTM and GRU techniques, achieving lower RMSE values of 0.045 for LSTM and 0.051 for GRU. Kim et al. focused on predicting the price of Ethereum using ANN and SVM. They obtained an RMSE of 0.068 and 0.048, respectively, indicating that SVM performed better in forecasting Ethereum prices.

Authors	Cryptocurrency	Techniques	RMSE
Pabuçcu et al	Bitcoin	ANN	0.341
Pabuçcu et al	Bitcoin	SVM	0.438
Pabuçcu et al	Bitcoin	Naïve Bayes	0.461
Pabuçcu et al	Bitcoin	RF	0.293
Jagannath et al	Bitcoin	LSTM	1.9
Awoke et al	Bitcoin	LSTM	0.045
Awoke et al	Bitcoin	GRU	0.051
(Kim et al., 2021b)	Ethereum	ANN	0.068
(Kim et al., 2021b)	Ethereum	SVM	0.048
This research	Bitcoin	Nadaraya–Watson kernel regression	0.17
This research	Dogecoin	Linear regression	0.032
This research	Ethereum	Gaussian regression	0.02
This research	USD coin	XGboost, Gaussian regression, Ridge	0.014
This research	Binance coin	Gaussian regression	0.032
This research	Cardano coin	LSTM	0.059

The proposed model achieved lower RMSE values for different cryptocurrencies using various techniques. The Nadaraya-Watson kernel regression technique provided an RMSE of 0.17 for Bitcoin, Linear Regression provided an RMSE of 0.032 for Dogecoin, Gaussian regression provided an RMSE of 0.02 for Ethereum, XGboost, Gaussian regression, and Ridge achieved an RMSE of 0.014 for USD coin, Gaussian regression provided an RMSE of 0.032 for Binance coin, and LSTM achieved an RMSE of 0.05 for Cardano coin.

DISCUSSION

The study results showcased the efficacy of various machine learning techniques in predicting cryptocurrency prices, with some simpler models outperforming complex ones. These findings align with existing literature, emphasizing the importance of model selection and the trade-off between complexity and performance. The proposed model demonstrated promising results based on the RMSE metric, highlighting its potential for practical applications in the financial industry.

Study Limitations: One limitation of this study is the reliance on historical price data, which may not fully account for unforeseen events or market fluctuations.

Additionally, the study focused on a limited number of cryptocurrencies and did not consider other potential factors such as market sentiment or regulatory changes. The choice of machine learning techniques could also be expanded to include more recent advancements or other ensemble methods.

CONCLUSION

This study examines the effectiveness of time-series prediction models for cryptocurrency prices, as machine learning and blockchain technology have gained attention in recent years. The research found that complex models for anticipating cryptocurrency prices may not perform better than a simple persistence model. The proposed model in the study had better performance on average, as evaluated by the RMSE. Future work could involve testing the models on different time frames or comparing their performance on different subsets of the data, and exploring other prediction models such as deep learning, recurrent neural networks, or reinforcement learning. There are many opportunities for future research in the field of cryptocurrency price prediction using ML.

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Muhammad Ali Mohammed

My name is Muhammad Ali Mohammed. I am doing my master's degree in Çankırı Karatekin University Computer Engineering Department. I am working on machine learning and cryptocurrencies.

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Power system fault detection and notification with Wi-Fi

Ümit Çatalca[1], Bahattin Emre Metin[1], Meral Özarslan Yatak[1], Çağdaş Hisar[2], Mustafa Teke[3]

[1]Department of Electric and Electronic Engineering, Faculty of Technology, Gazi University, Ankara, Türkiye
[2]Department of Automotive Engineering, Faculty of Technology, Gazi University, Ankara, Türkiye
[3]Department of Electric and Electronic Engineering, Faculty of Engineering, Çankırı University, Çankırı, Türkiye

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Corresponding Author: Meral Özarslan Yatak, ozarslanm@gazi.edu.tr

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ABSTRACT

In this study, a prototype model was designed and implemented for power system failure. A mobile application was developed for notification of faults that may occur in power systems. The line current data was transmitted with Wi-Fi via module on mobile application and so negative impacts of the production sector was eliminated and the ordinary flow of life by minimizing the duration of power outages due to technical failures were prevented. By measuring the current in the prototype, it was possible to determine a short circuit situation, and to warn the operator with the mobile application on the mobile phone, and then to quickly dispatch them to the defective area. Protection in the power system is carried out more healthily with instant data flow with the mobile application.

Keywords: Power system fault, Wi – Fi, mobile application

INTRODUCTION

Power systems and wireless communication are two different but related areas of electrical engineering. The production, transmission, and distribution of electrical energy are all concerns with power systems. They entail designing and putting in place the electrical infrastructure necessary to guarantee the secure and effective transport of electricity from generators to consumers. Power systems come in a variety of sizes, from tiny microgrids to massive, globally interconnected grids. Generators, transformers, transmission lines, and distribution networks make up the foundation of a power system (Ilic et al., 2004).

Wireless communication is a rapidly expanding field that has completely changed the way people obtain information and communicate. Mobile telephony, wireless local area networks (WLANs), and satellite communication are just a few of the uses for wireless communication systems (Hussain et al., 2020). Power systems and wireless technology are actually tightly related, despite their initial discordance. Considering the criticality of the power systems, it can be said that the occurrence of any fault affects the users negatively. A power systems depend on wireless communication for the remote monitoring and management of electrical infrastructure, while wireless communication depends on power systems for the electrical energy required to run communication equipment. Therefore, for the design and operation of contemporary, effective, and trustworthy electrical systems, a solid understanding of both power systems and wireless communication is necessary.

A power system fault is an abnormal condition that occurs in an electrical power system, causing a disruption in the normal functioning of the system. Faults in power systems can occur due to various reasons such as equipment failure, human error, natural disasters, and other reasons. It's important to detect and isolate faults in a power system as soon as possible to avoid equipment damage and to minimize the disruption of power supply to the customers. These faults must be informed to the operator via the fastest communication channel and they must be sent to the fault location for intervention.

There are various wireless communication systems and tools for power system failure notification as SCADA (Supervisory Control and Data Acquisition) interface system, Bluetooth, GSM (Global System for Mobile Communications), and Wi-Fi (Wireless Fidelity) etc. in the literature (Abir et al., 2021). Fault monitoring method over SCADA is currently used for fault notification in power systems (Ortiz et al., 2016). SCADA is a type of industrial control system that is used to monitor and control industrial processes and infrastructure such as power generation and distribution, water and wastewater treatment, oil and gas pipelines, and manufacturing operations. SCADA systems typically consist of a central computer or server that collects data from a network of remote devices and sensors. While SCADA system offers many benefits, it has also some disadvantages to consider as cost, complexity, security risks, data overload, and latency. A system that employs Bluetooth technology to transmit alerts of defects or alarms from remote devices to a central control station is known as a Bluetooth-based fault notification system. Remote devices in this kind of system, including sensors, actuators, and other control elements, are outfitted with Bluetooth radios that enable wireless communication with a central control station. A GSM-based power system fault notification system uses a GSM network to send notifications of faults or alarms from remote devices to a central control station.

Wi-Fi (based on IEEE 802.11) wireless communication technology is preferred for fault notification in addition to GSM and Bluetooth. As Wi-Fi has a much larger range compared to both GSM and Bluetooth. Wi-Fi allows multiple devices to connect to the same network at the same time, while both GSM and Bluetooth are designed to connect only two devices at a time.

Nur et al. (2014, 2014) designed a system to detect the transmission line fault for the user via Bluetooth and GSM to easily recognize the current condition of the distribution line. They could monitor the distribution line status continuously and hence guard the fault of distribution line due to the constraints. Tan et al. (2007) designed a prototype of GSM automatic power meter reading system. Ojo et al. (2022) implemented a GSM-based Monitoring System for a Distribution Transformer. This system contains a server module that receives and stores transformer parameter information from all of a utility's distribution transformers in a database application regularly. Bekiroglu and Daldal(2009) developed a microcontroller-based, remote monitoring and automation system for distribution transformers operating in medium voltage networks.

Wireless fault monitoring is also very important for renewable power systems. A failure detection system for solar module arrays was created by Chao et al. (2022). They linked a fault detection module to the Wi-Fi on the case site, mounted it in the junction box on the rear of each photovoltaic module (PVM), and transferred data and information to the server for data analysis. The maintenance staff was immediately informed of the PVM's data results through an exception alert notification, allowing them to promptly rule out any potential failures. Real-time implementation of the prototype model for the street lights' failure was realized by Rani et al. (2016). The fault was detected and it was intimated by vehicle containing Wi-Fi.

In this study, a prototype model was designed and implemented for power system failure. A mobile application was developed. With this project, it is determined that a short circuit occurs in the transmission line based on the rising or falling current values or voltage values in case of any failure. The data received from the current sensor is transferred to the microcontroller and after the values are compared, it is transmitted to the mobile application over the internet. In case of malfunctions, an audible warning sounds in the mobile application and the measured values are displayed. With this project, the technical team is informed about the malfunction through the application installed on the mobile device they are using without waiting for any notice. The faster you are aware of the fault, the faster the solution will be. The disruption of the normal flow of life due to a power outage is reduced to even shorter time. With this rapid communication, the rate of disruption in the production sector is also reduced.

Wireless Communication Methods for Power System Failure

A notification of a power system fault normally refers to an alarm or warning that there is an issue with the electrical power system. This could be a simple problem, like a broken fuse, or a serious issue, like a power outage. The alert could be conveyed electronically to a control center, as a visible or aural indication, or both. To avoid potential danger to equipment and workers, as well as to save downtime and disruption to operations, it is crucial to act quickly in the case of a power system malfunction notification. Depending on how serious the defect is, the right course of action can be to reset a circuit breaker, replace a blown fuse, or turn off the device until it can be safely fixed.

Although SCADA systems provide many advantages, there are also drawbacks to take into account as especially cost and security risks. SCADA systems are susceptible to cyberattacks. Also, SCADA systems produce a lot of data, which can be challenging to manage and evaluate. As an alternative for failure notification, Bluetooth or GSM can be preferred. When a fault is detected by a remote device, a notification is sent to the control station over the Bluetooth and GSM connection. The control station then processes the notification and can take appropriate actions, such as triggering an alarm or sending a message. However, like any wireless system, Bluetooth-based and GSM-based fault notification systems can be at risk to interference and security risks.

The wireless industry is currently dominated by the Bluetooth and Wi-Fi protocols, which specify the physical layer and medium access control (MAC) for wireless communications over short action ranges (from a few to several hundred meters) and with low power consumption (from less than 1 mW to hundreds of milliwatts).The standards cover a variety of techniques at the physical layer, including infrared communications and various radio signal multiplexing techniques, including complementary code keying (CCK), orthogonal frequency-division multiplexing (OFDM), direct sequence spread spectrum (DSSS), which is used in IEEE 802.11 commercial devices, and frequency hopping spread spectrum (FHSS), which is used by Bluetooth devices (Potorti& Ferro, 2005).

The aim of the IEEE 802.11 standard (Wi-Fi) is to provide wireless connectivity to devices that require quick installation, such as portable computers, PDAs, or generally mobile devices inside a wireless local area network (WLAN). The range of Wi-Fi is larger and the speed is faster than GSM and Bluetooth. Considering these features, Wi-Fi was used for fault notification in this study.

Power System Prototype and Fault Detection Hardware Design

Potential failures can be reduced with robust design, proper operating conditions, and regular equipment maintenance in power systems. However, possible malfunctions are not completely eliminated. In this case, it is important to protect the network elements from failures as much as possible. Protection relays are used to prevent faults in power systems. In case of a fault in the system, the relay closest to the fault will detect the fault and open the breaker in the circuit and cut the power of the faulty section. After removing the faulty place from the system, maintenance teams will be provided to fix the fault. Fast and accurate fault detection extends equipment life by eliminating mechanical effects caused by high currents and heating.

In this study, a transmission line with 1 phase and 1 neutral was implemented as a prototype. As a consumer, AC Motor was added to the end of the system as a load. The current value for the load was adjusted by an AC chopper. It was assumed that a short circuit occurred when the current drawn by the motor in the system exceeds 1.5 Amps. This was an obvious increase in current in the flowing current in case of any short circuit that may occur in the transmission line. This value was entered into the system as a reference value with the codes run with the Arduino IDE software. Through the Wi-Fi Module, instant data flow from the system could be followed over the designed mobile application. Firebase Database was used as database. If the current value exceeded 1.5 A, a warning was sent to the mobile application and as a result of this warning, the system was automatically deactivated and an audible alarm sounded in mobile application. In addition, it was seen on the mobile application that the energy of the system is automatically cut off.

A fault that might occur in the transmission line was transmitted instantly with the mobile application installed on the mobile phone used by the fault repair team, in this way, dispatching the team for repair was very fast.

The designed and implemented power system failure detection system via Wi–Fi can be seen from **Figure 1.** The equipment list used for the system is shown in **Table 1.**

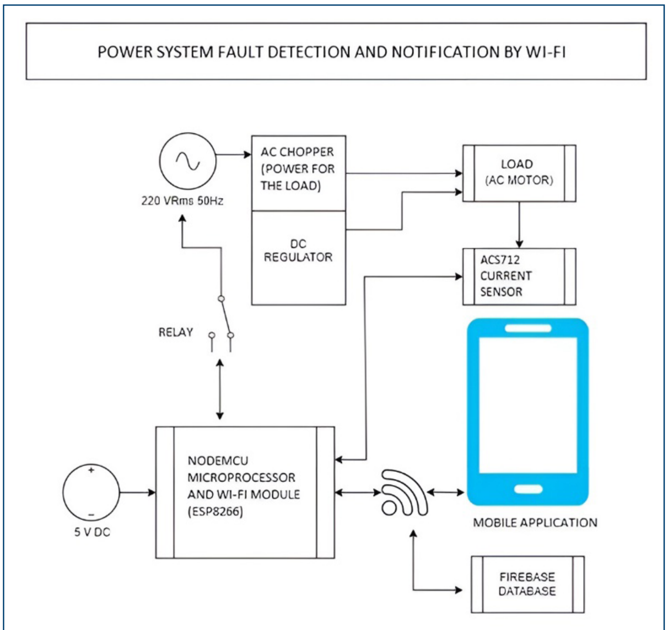


Figure 1. Block diagram of the implemented system.

Table 1. The equipment list used for the power system fault detection prototype

	Equipment	Property
1	Microcontroller with W-Fi module	NodeMCU V3 ESP8266 ESP-12E
2	Current Sensor	ACS712
3	Load	AC Motor
4	AC Clamper	Circuit with triac
5	Regulator	Excitation
6	Power Supply	18 V Adapter
7	Computer	Installed Arduino IDE
8	Telephone	Installed Mobile Application
9	Relay	SRD-05VDC-SL-C

The developed algorithm can be seen from **Figure 2**. As seen from this flowchart that, the operation condition is written on the mobile screen as "System ON" or "System OFF". The current data is obtained from ACS712 current sensor and if there is a short circuit; the system changes the position as alarm. The system is disabled automatically and an alarm is run.

NodeMCU was used as a microcontroller. This open-source firmware and development kit is appropriate for prototype. The module is based on ESP-12/ESP8266 Wi-Fi Module. Module integrates 3.3V Regulator, GPIO, PWM, IIC, 1-Wire and ADC all in one board. One ADC channel was used for this project for reading the current. The pinots of the microcontroller can be seen from **Figure 3.**

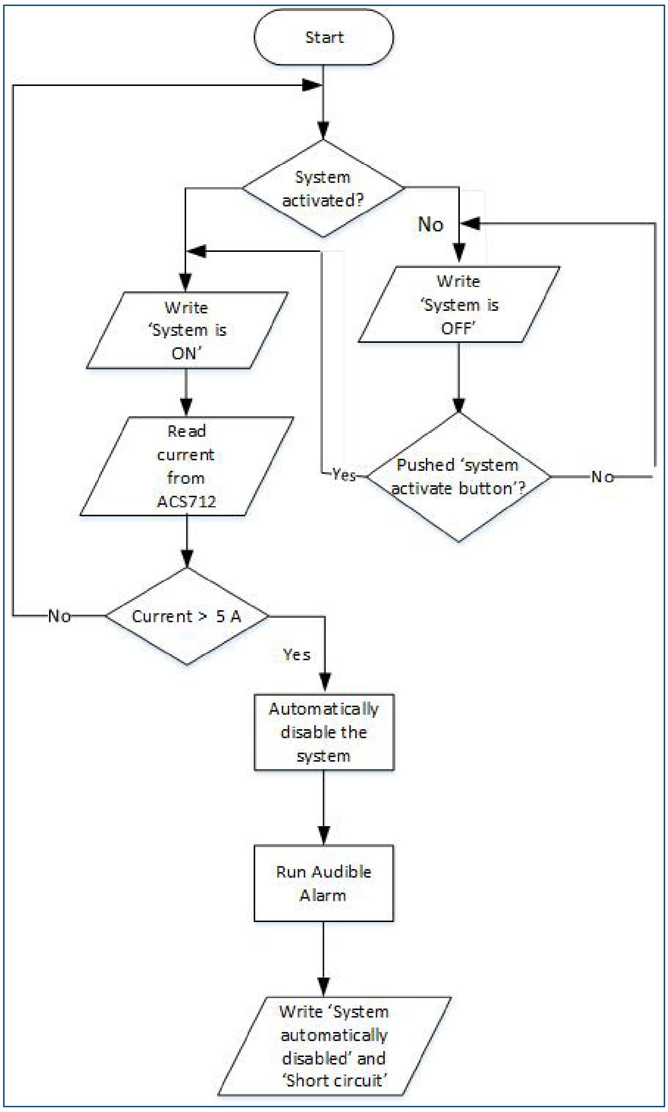


Figure 2. The flowchart of the study.

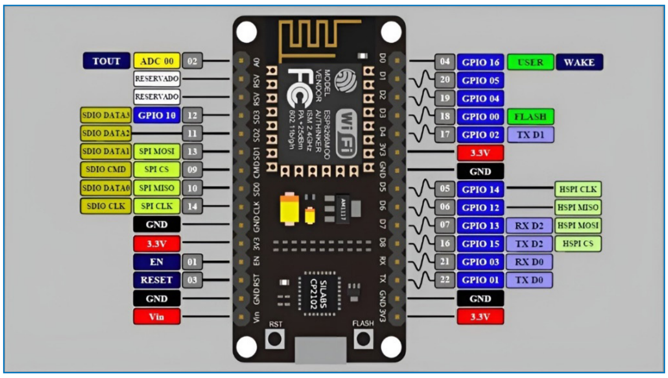


Figure 3. NodeMCU Pinout.

ACS712 current sensor was used to sense the line current. The board is a simple carrier of Allegro's ±30 A ACS712T ELC-5B Hall effect-based linear current sensor.

Switching capacity of the SRD relay is available by 10A in spite of small size design. It was used to cut the current in an abnormal condition.

The prototype of the implemented power system failure detection system via Wi–Fi can be seen from **Figure 4.**

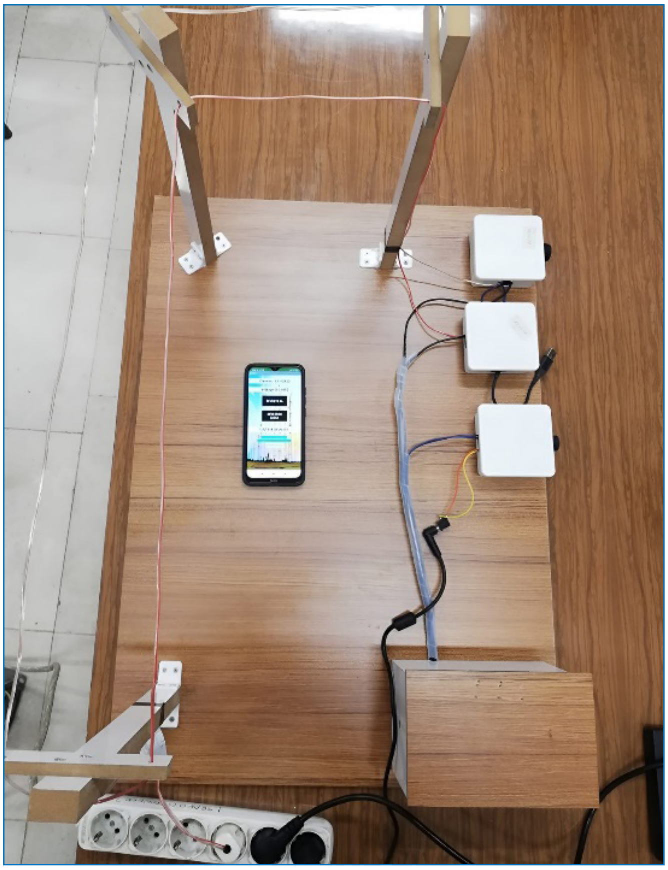


Figure 4. The prototype of the implemented system.

RESULTS AND DISCUSSION

Wi-Fi technology was developed and widely adopted with considerable help from IEEE 802.11, allowing for wireless access and communication in a variety of situations and devices. In this study, a Wi – Fi module with an inner antenna was used to easily connect to Wi-Fi network environment. It can transmit and receive data packages. Wi-Fi networks can provide fast data transfer speeds, allowing users to download and upload.

The mobile application interface was designed with APPINVENTOR. The developed codes can be seen from **Figure 5.**

Line current data was transferred to the system instantly The developed mobile interface screenshot for normal operation situation can be seen from **Figure 6**. If the current flow exceeded 1.5 A, which was defined in the software, the system was automatically deactivated and gave a warning on the mobile application as "System Disabled Automatically". In addition, a warning appeared on the screen as "Short Circuit in the System" and an audible alarm sounds. This situation screenshot can be seen form Figure 7. While the normal values were present, the note "System Enabled" appeared on the screen. If required, the system could be activated and deactivated manually via the mobile application for activities such as maintenance/repair.

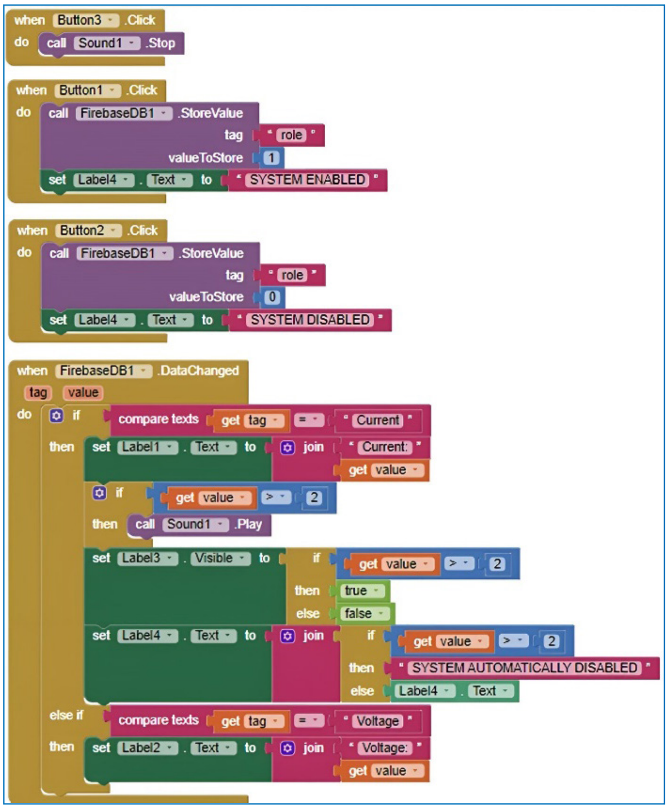
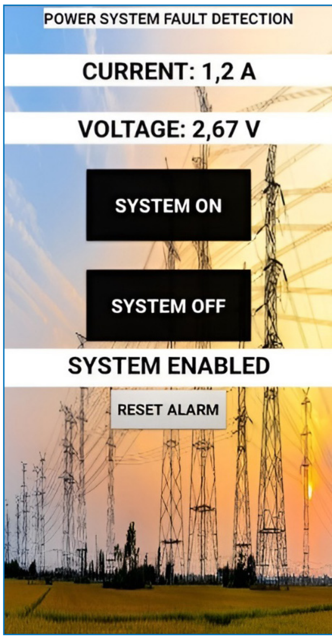


Figure 5. Developed mobile application codes.



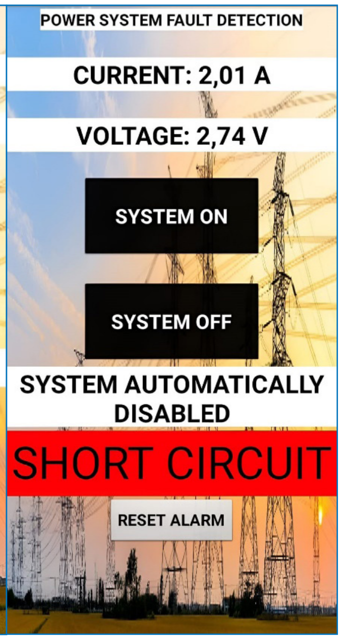


Figure 6. Screenshot for normal operation condition

Figure 7. Screenshot for fault condition

CONCLUSION

The operator team should be sent to the defective location as soon as possible in order to fix the primary faults that may arise during energy transmission and distribution. When a failure occurs, the fault notification process may be delayed as most of current detection systems are based on SCADA system. In this case, it slows down and interrupts the normal flow of life and the production sector. In this study, the process could be faster considering Wi–Fi communication. By measuring the current in the prototype with ACS712, it was possible to determine a short circuit situation that may occur on the line, and to warn the operator with the mobile application on the mobile phone, and then to quickly dispatch them to the defective area. The system is appropriate for adding some useful functions. In the future, the system power will be measured and will be monitored on the mobile application. Additionally, the condition of the circuit breaker and disconnector may be displayed on the application,

ETHICAL DECLARATIONS

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Ümit Çatalca

He works on electrical power systems. He is currently an electrical and electronics engineering student at Gazi University. He completed his summer internship as an Electrical Substation Operation and Automation engineer at the RİNO Söğütsen ceramics factory. He is also graduate of business administration. The Turkuaz Hyperloop Team, in which he is a member, won the first place in the hyperloop development competition held in Türkiye. As a thesis work in the field of electrical and electronic engineering, he performed Power System Fault Detection with Mobile Application and notification by Wi-Fi.

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Review

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Faculty network system implementation using Cisco packet tracer

Özge Ersoy Cangir, Mustafa Yıldırım, Nurgül Bostan

Department of Computer Engineering, Faculty of Engineering, Çankırı Karatekin University, Çankırı, Turkey

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Corresponding Author: Özge Ersoy Cangir, ozgecangir2@gmail.com

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ABSTRACT

In this study, the faculty network system was designed using the Cisco Packet Tracer program without the use of any physical components. The aim was to simulate the network structure of the faculty to show the engineering faculty on the campus map and enable communication between the computers within the faculty by configuring similar devices with real router, switch, and server configurations. The management of IP configurations of the devices in the network structure and the configuration of the router, switch, and servers (DNS, DHCP, FTP, HTTP, and MAIL) used in the network were implemented in the Cisco Packet Tracer environment to create a simulated network system that can be applied in real systems.

Keywords: Cisco packet tracer, network simulation, university network system

INTRODUCTION

In today's world, the steps involved in creating a network architecture have become an overlooked aspect due to increasing costs. However, design and implementation programs are extremely important for placing network resources in the appropriate position, testing and updating the network system. One of these programs is Cisco Packet Tracer. Cisco Packet Tracer is a simulation program that allows Cisco operations or applications to be performed without the use of any physical machine or tool, providing us with a network laboratory environment [1]. It serves as a design screen to explore networks. It is essential to provide network learning and practical tools for students to simulate or create and manage systems to better understand the philosophy behind networks [2]. Since protocols are implemented only in software, this program cannot replace hardware routers or switches. However, this tool includes not only Cisco hardware but also a wide range of other network devices. This program:

- Supports a multi-user system that allows many users to connect various topologies over a computer network.
- Provides visual presentation, animation, and testing and modeling of difficult and time-consuming projects.
- Has simulation, visualization, evaluation, and control capabilities for networks and peripherals.
- Has logical and physical working areas.

Logical Workspace

The logical workspace displays the logical network topology created by the user. It is used to view the connecting, placement, and clustering of virtual network devices.

Physical Workspace

In the physical workspace, we can see a physical implementation of the logical network. It also shows us how network devices such as switches, routers, and hosts are connected in a real network topology.

DHCP Server (Dynamic Host Configuration Protocol Server)

Provides automatic and centralized management for the distribution of IP addresses within a network. It creates a pool of IP addresses and leases addresses to any DHCP-enabled client when started on the network. Because IP addresses are dynamic rather than static, when an address is no longer used, it is automatically sent back to the pool for reallocation. In short, they are devices that automatically perform all the necessary configurations so that the devices on the network can communicate with each other and reach external networks, and ensure that each device has a unique IP address [3].

DNS Server (Domain Name System Server)

IP addresses are identity-like structures based on a specific protocol, consisting of number blocks, used to distinguish web sites and users on the internet [4]. Web pages on the Internet have their own unique IP addresses, and all users connected to the Internet are assigned an IP address. It's impossible for people to remember that many IP addresses. To solve this problem, the domain name system was created and the problem was eliminated with the DNS servers running in the system. The goal is to translate what a user types into a browser into a language the computer can understand and an address that they can use to find a website.

FTP Server (File Transfer Protocol Server)

It is a service structure that allows FTP users to access files on remote computers [5]. It is a standard network protocol used to transfer files between a client and server in a computer network. It also enables communication between computers on the Internet. One computer acts as a server to store information and the other acts as a client to send or request files from the server. FTP server, which provides data exchange and connection between computers at the same time, creates instant information flow.

Web Server

It is a TCP/IP based communication protocol used to present data in the network environment. Websites serve with the IP of these servers and the content on them [6]. This server presents the files on the websites to the users using the HTTP protocol, responds to each request of the users and executes them by the automatic mechanisms of the computers.

Mail Server

It is the server that establishes e-mail communication between local and remote users and provides control and management of this process. Mail Server can act as a separate machine, or any domain within a Web Server can be configured as a Mail Server. Although mail sending seems to happen very quickly, in the background there are many checks, authorizations, transfer over layers in the internet protocol, sometimes encryption and decryption, and then communication between servers. By defining the domain name, user names and passwords on this server, the e-mail service is activated within the network, allowing users to send e-mails to each other within the network [7].

The work flow diagram of the study is shown in **Figure 1**.

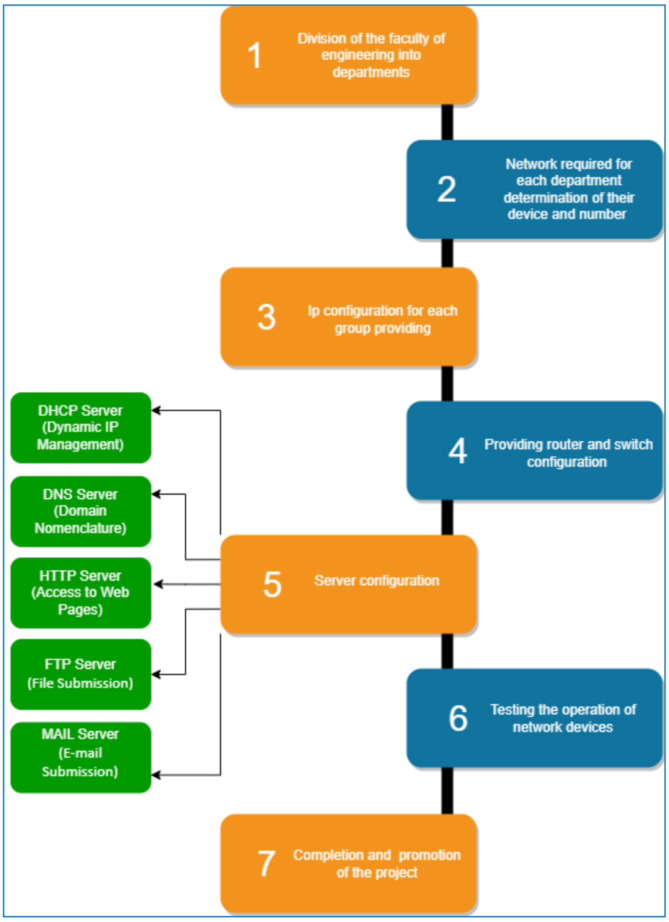

Figure 1. Workflow diagram of the proposed system.

METHODS

Network Components

In the designed simulation, DSL modem, router, switches, access points, servers, IP phone, computers and printers were used on the Cisco Packet Tracer program. The number and types of servers are variable according to the needs, and the design was carried out using base servers in this structure [8].

Network Configuration

In the study, a real network topology was designed, all configurations were realized and a local area network (LAN) is created. LANs provide computer users with many conveniences such as shared access to devices and applications, file sharing among connected users, and communication between users [9].

In **Figure 2**, the design of the overall network topology is given.

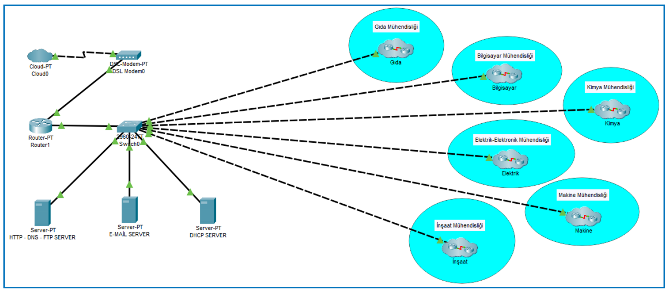

Figure 2. Designed network topology.

IP Configuration

In growing network topologies, dynamic IP distribution is made to clients using a DHCP Server, as manually configuring TCP/IP settings of network devices would be a waste of time.

Figure 3 shows a computer with a static IP assignment.

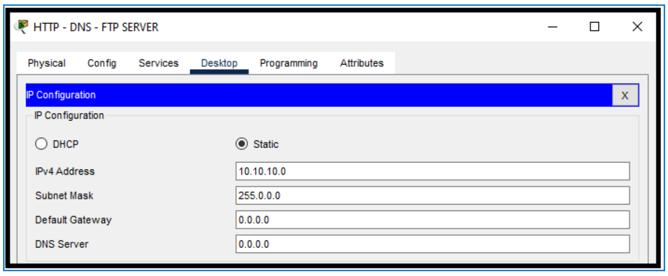

Figure 3. Static IP assigned computer.

Router Configuration

As a result of the physical connections between the devices, the devices are only physically connected to each other, but this is not enough for the devices to communicate with each other because the interface configurations of the devices must also be made [10].

The router configuration is shown in **Figure 4**.

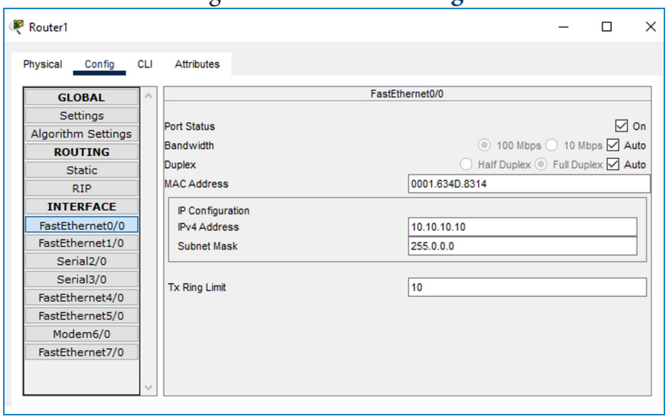

Figure 4. Router configuration.

Switch Configuration

Each switch is configured with a password. Username and password are assigned. Password must be entered to access/modify the IOS command line interface [11].

Figure 5 shows the commands used in the CLI console where the switch is configured.

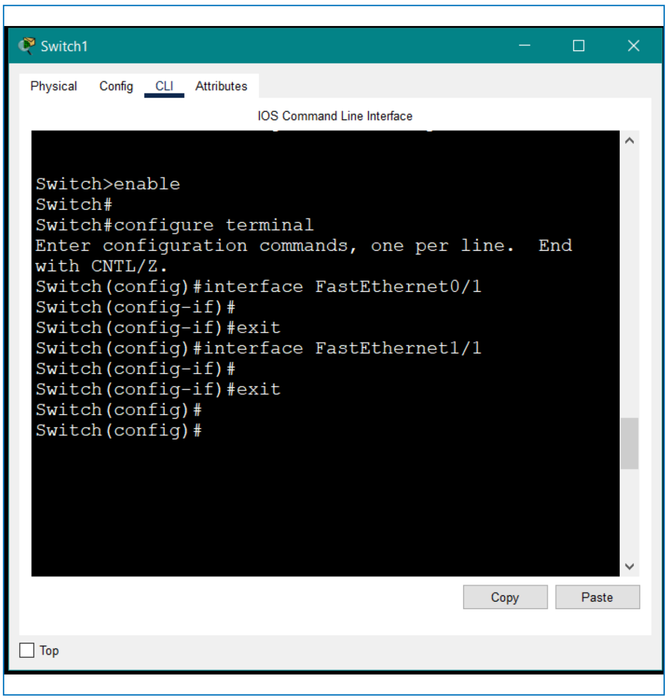

Figure 5. Switch configuration.

Server Configurations

It is shown in **Figure 6** that the e-mail addresses are defined and in **Figure 7**, the mail is successfully transmitted from one user to another with the Mail Server connection.

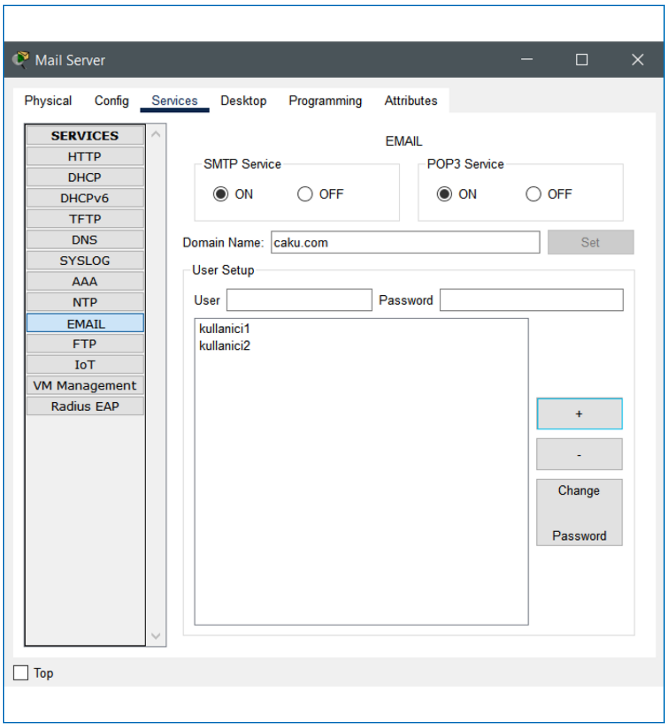

Figure 6. Defining e-mail addresses.

We configured it with a DHCP server to provide IP addresses to PCs [12].

In **Figure 8**, it is shown that the IP distribution takes place statically by configuring the DHCP Server.

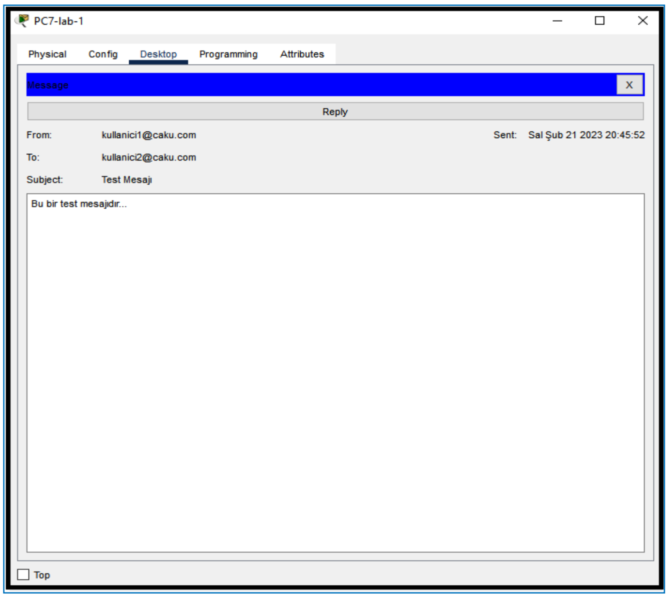

Figure 7. Mail Server connection.

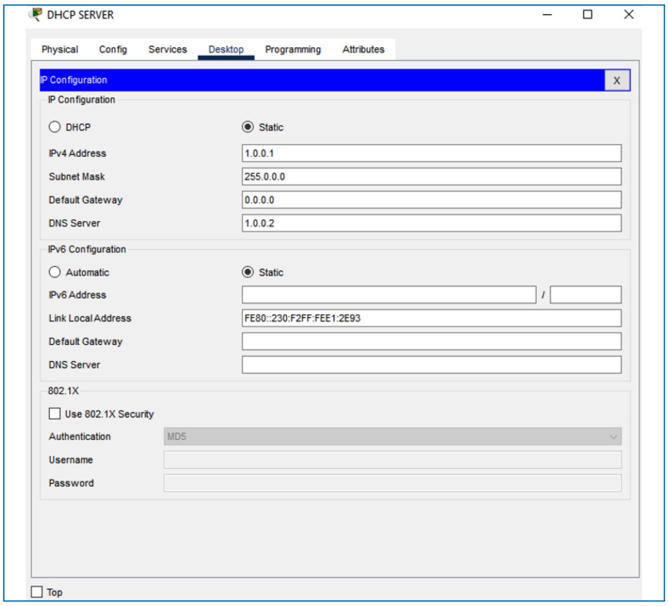

Figure 8. DHCP Server pools.

In **Figure 9**, it is shown that connection to a website can be provided by configuring the Web Server.

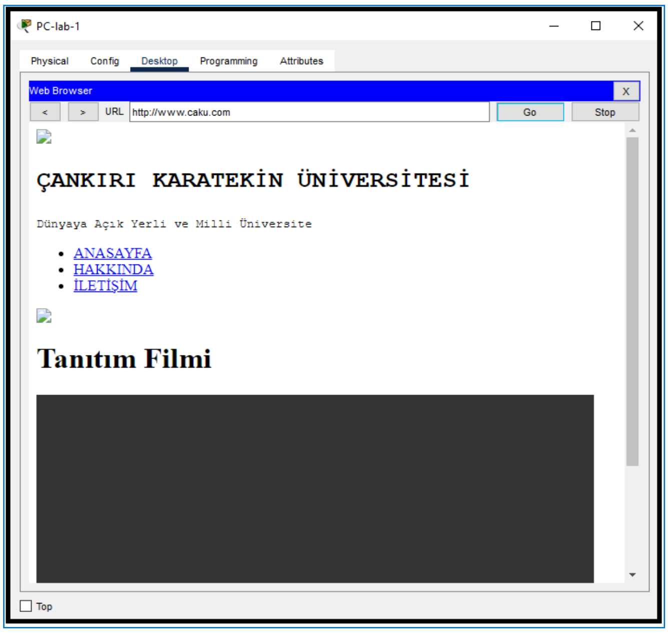

Figure 9. Web Server connection.

The command prompt in **Figure 10** shows the configuration of the FTP server and the file transfer process.

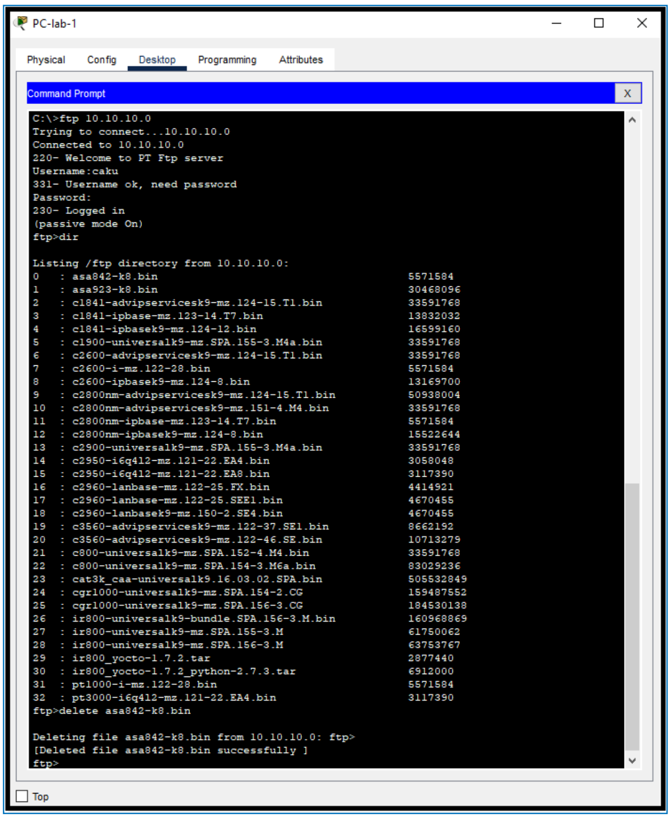

Figure 10. FTP Server connection.

DNS Server configuration is shown in **Figure 11**.

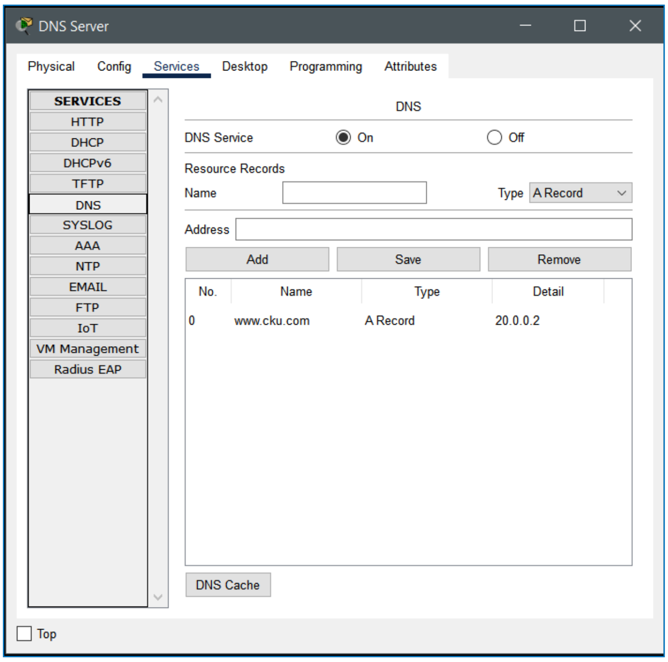

Figure 11. DNS Server configuration.

RESULTS AND DISCUSSION

This study involved designing a local area network that includes routers, switches, IP phones, access points, modems, and necessary servers. Cisco Packet Tracer program was used during the project and device configurations were identical to those of real routers and switches. VLANs were defined and configured on the necessary devices. A DHCP server was defined for computers, and IP addresses were observed to be assigned to them. A DHCP pool was created for IP phones. Configurations were made on the routers, and it was observed that the networks communicated with each other. A DNS server was defined and distributed to computers via DHCP pools. An HTTP server was defined and accessibility was observed. Access lists were defined to determine which networks could be accessed and which ones could not, and which devices could access which devices were also determined. An FTP server was defined, and it was observed that file sharing was possible between computers. A mail server was set up by defining domain names, usernames, and passwords, and it was observed that users were able to send emails to each other within the network. In the simulation results, it was seen that a packet can travel smoothly between the source and destination. Configurations were completed flawlessly within the determined rules, and a local area network was created.

CONCLUSION

This study was conducted using the Cisco Packet Tracer application, and therefore did not incur any costs. This application enabled testing of both servers and network devices. The study can be further developed and applied to all faculties of the university, and even to other universities. The number of network devices that can be used in reality cannot be replicated in the study, and physical conditions are not present. As the application eliminates physical conditions, it cannot fully reflect reality..

ETHICAL DECLARATIONS

Referee Evaluation Process: Externally peer-reviewed.

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Özge Ersoy Cangir

Özge Ersoy Cangir is currently studying at the Department of Computer Engineering at Çankırı Karatekin University in the last year. I graduated from Gazi University, Department of Statistics in 2009. I am dealing with artificial intelligence, medicine, cyber security, image and sound processing fields.