International Journal of

ADVANCES IN ARTIFICIAL INTELLIGENCE RESEARCH

Volume 2, Issue 1, 2022
ISSN: 2757-7422

International Journal of ADVANCES IN ARTIFICIAL INTELLIGENCE RESEARCH

AAIR

Advances in Artificial Intelligence Research

https://dergipark.org.tr/aair

Date of Publication	February 2022
Language	English
Frequency	Published twice in a year
Graphic designer	Özden Işıktaş
Correspondence Address	Muğla Sıtkı Koçman University, Faculty of Technology, Information Systems Engineering, 48000 Kötekli/MUĞLA
Phone	0 506 4887818 – 0252 211 5526
Correspondence Mail	osmanozkaraca@mu.edu.tr

International Journal of
ADVANCES IN
ARTIFICIAL
INTELLIGENCE
RESEARCH
AAIR

Table of Contents

Advances in Artificial Intelligence Research (AAIR)
ISSN 2757-7422
www.dergipark.com/aair/

Vol. 2 (No. 1), pp. 1-6, 2022
doi: 10.54569/aair.1016544
Published online: Feb 16, 2022

Importance of Preprocessing in Histopathology Image Classification Using Deep Convolutional Neural Network

Nilgün Şengöz [1, *], Tuncay Yiğit [2], Özlem Özmen [3], Ali Hakan Işık [4]

[1] Burdur Mehmet Akif Ersoy University, Burdur, Turkey;
[2] Süleyman Demirel University, Dept. of Computer Engineering, Isparta, Turkey;
[3] Burdur Mehmet Akif Ersoy University, Dept. of Pathology, Burdur, Turkey;
[4] Burdur Mehmet Akif Ersoy University, Dept. of Computer Engineering, Burdur, Turkey;

Abstract

The aim of this study is to propose an alternative and hybrid solution method for diagnosing the disease from histopathology images taken from animals with paratuberculosis and intact intestine. In detail, the hybrid method is based on using both image processing and deep learning for better results. Reliable disease detection from histo-pathology images is known as an open problem in medical image processing and alternative solutions need to be developed. In this context, 520 histopathology images were collected in a joint study with Burdur Mehmet Akif Ersoy University, Faculty of Veterinary Medicine, and Department of Pathology. Manually detecting and interpreting these images requires expertise and a lot of processing time. For this reason, veterinarians, especially newly recruited physicians, have a great need for imaging and computer vision systems in the development of detection and treatment methods for this disease. The proposed solution method in this study is to use the CLAHE method and image processing together. After this preprocessing, the diagnosis is made by classifying a convolutional neural network sup-ported by the VGG-16 architecture. This method uses completely original dataset images. Two types of systems were applied for the evaluation parameters. While the F1 Score was 93% in the method classified without data preprocessing, it was 98% in the method that was preprocessed with the CLAHE method.

Keywords: *Artificial Intelligence, CLAHE, Deep Learning, Histopathology Image*.

1. Introduction

In the age of Artificial Intelligence (AI), the analysis of visual information has be-come an important reality, enabling machines to process the information contained in images. In this context, it has a rapidly expanding field in many different applications such as security, transportation and health (diagnosis) in order to accelerate decision-making and analysis processes. In particular, the need for greater efficiency in image processing and analysis has become important due to the increasing volume of image data and increasingly difficult computational tasks.

Deep learning is a part of machine learning and is a special type of artificial neural network (ANN) that resembles a multi-layered human cognition system. Deep learning is of great interest today due to its use with large healthcare data. Although ANN was introduced in 1950, its training posed serious limitations and problems for solving problems due to problems such as lack of computational power and lack of sufficient data. However, given the current availability of big data today, advanced computing power with graphics processing units (GPU), and new algorithms for training a deep neural network (DNN), many limitations and problems have been resolved. In this context, deep learning approaches show impressive performances in imitating humans in various fields, including medical imaging.

Image and video processing finds wide application in medical science. Biomedical imaging techniques have an important role in both diagnosis and treatment. These techniques have significantly helped improve patients' health care. Image-guided therapy has significantly reduced the risk of human error with improved accuracy in disease detection and surgical procedures. The history of medical imaging began in the 1890s and has gradually risen thanks to today's technological infrastructure and accessible datasets.

Histopathology diagnoses diseases occurring in tissues/cells by examining tissues and cells under a microscope. In addition to diagnosing disease, histopathologists assist clinicians with patient care and management.

Digital pathology (DP) is the process by which histology slides are digitized to pro-duce high resolution images. It is becoming very popular in the field of medical imaging research. By transferring microscopic digital images to a computer pro-gram, early diagnosis and treatment methods can be developed, thus providing great benefits to both pathologists and patients. For this reason, histopathology imaging applications attract significant attention from the research community due to their rapid and effective nature. By transferring

*Corresponding author
E-mail address: nilgunsengoz@mehmetakif.edu.tr

Received: 11/Nov/2021; Received in revised form: 20/Dec/2021; Accepted: 04/Jan/2022.

microscopic images to digital media in the laboratory environment by pathologists, the use of Artificial Intelligence algorithms in disease detection, segmentation and classification problems has been enabled.

In this study, detailed information about Paratuberculosis disease in animals will be given, and then the contribution of the CLAHE method, which is one of the preprocessing techniques used, to the learning algorithm will be examined.

2. Definition and Significance of the Disease

Paratuberculosis, Mycobacterium avium subsp. It is a chronic and contagious disease caused by paratuberculosis (pTB). The disease is present worldwide and mainly affects ruminant (cows, cattle, etc.) animals, but has also been found in various animal species including horses, pigs and rabbits. [2] The worst part of pTB disease is that this type, which was first encountered in 1892, unfortunately still has not been found to have a vaccine and there is no effective treatment method currently available.

The age of the animal is a very important factor in pTB. Cattle develop resistance with age and are often infected as calves. However, age-related resistance can be overcome by infectious pressure. Moreover, the rate of detectable infections in-creases with the age of the animal. These disease traits, combined with the progressive nature of pTB, mean that the age distribution of herds plays an important role in pTB dynamics. PTB causes significant economic losses. Most important ones; Substitution costs due to increased culling, increased mortality, de-creased milk production and reproductive performance, decreased slaughter value and higher susceptibility to other diseases [3].

The economic loss associated with pTB has been estimated at $20-50 per cow in infected herds. In the United States, the infection causes an annual economic loss of more than 1.5 billion dollars. In France, the average loss associated with a clinical case was EUR 1940, while each subclinical case resulted in an estimated loss of EUR 461 [4, 5]. According to a study conducted in Hungary, the economic loss from the increased culling and mortality rate of pTB seropositive cows is EUR 166 per cow. In addition to the resulting economic losses, it has been reported that the control of pTB is not only in animal health but also in the etiology of Crohn's disease seen in humans, and that pTB can be transmitted from infected animals to humans by consuming dairy products such as cheese, yogurt, cream, butter, ice cream as well as meat products [6]. However, Crohn's patients are 7.01 times more likely to detect MAP DNA compared to controls [7]. Therefore, measures to prevent MAP from entering the food chain are beneficial.

pTB is an OIE (World Organization for Animal Health) listed disease, and in a recent review of pTB control programs in 48 countries, 73% of the countries studied considered paratuberculosis to be a notifiable disease in dairy cattle. In addition, 46% of the countries surveyed in this report have an established control program. The most common reasons for having a control program include the impact of pTB on animal health, production losses, trade restrictions and animal welfare and public health concerns. The most common pTB control programs rely on a combined testing and evaluation scheme, with breaking the transmission routes within and between flocks. However, basic data on the true prevalence of pTB infection (community incidence of the disease) are needed to evaluate the effectiveness of a paratuberculosis control program [8]. Unfortunately, there is no active program against the disease in our country, and there is no union/association, etc., organized specifically for this disease, as in other countries.

With the ELISA test, the seroprevalence of pTB in the Burdur region was 6.2%, while the farm prevalence of pTB was evaluated in the study conducted in and around Burdur province, and it was determined as 58% (14/24). The prevalence of pTB in Burdur region was determined as 6.2% in Holstein cattle [9].

The aim of this study is to propose an alternative and hybrid solution method for disease diagnosis from histopathology images taken from animals with paratuberculosis and intact intestine. In detail, the hybrid method is based on using both image processing and deep learning for better results. Reliable disease detection from histopathology images is known as an open problem in medical image processing and alternative solutions need to be developed.

3. Material and Method

3.1. Overview of Deep Neural Network

Deep learning uses artificial neural networks to perform complex calculations on large amounts of data. It is a kind of machine learning that works according to the structure and function of the human brain. Industries such as healthcare, e-commerce, entertainment, and advertising often use deep learning algorithms.

While deep learning algorithms have self-learning representations, they depend on Artificial Neural Networks that reflect the way the brain computes information. During the training process, algorithms use unknown elements in the input distribution to extract features, group objects, and discover useful data patterns. Like training machines for self-learning, this happens on multiple levels, using algorithms to build the models. Deep learning models make use of several algorithms. While no single network is considered perfect, some algorithms are better suited for performing certain tasks.

3.2. Convolutional Neural Network

Convolutional neural networks (CNN) have gained special status in the last few years as a particularly promising form of deep learning. Rooted in image processing, convolutional layers have penetrated almost all subfields of deep learning and are often very successful.

CNN has been applied in various applications recently due to its feature extraction, pattern detection and classification capabilities.

CNN's main architecture consists of two basic parts; a feature extractor and a classifier. The feature extractor, in turn, consists of several linked layers. CNNs consist of convolution layer (Conv), pool layers, activation function and fully connected layer [10].

Due to their ability to learn highly complex features of image data [11], CNNs have been shown in recent years to be very successful in various image classification [12-14] and object detection [15] tasks. In the current literature, the most common deep learning techniques applied to computer vision applications are based on CNNs [16].

Fully convolutional networks (FCA) are a variation of CNNs. FCA architectures only consist of convolution and pooling layers (and possible deconvolution and upsampling layers), but ultimately do not include fully connected layers. The out-put of an FCA is usually the same size as its input. For segmentation/segmentation tasks, these intensive prediction models have provided significant improvements in both efficiency and accuracy. Figure 1 and Figure 2 show example architectures for a CNN and an FCA [17].

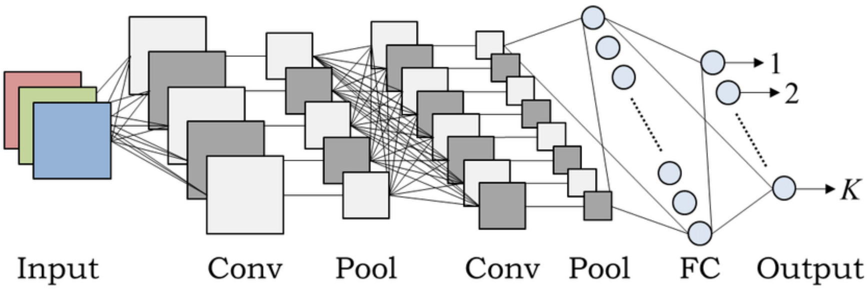


Figure 1. *Basic CNN Architecture*

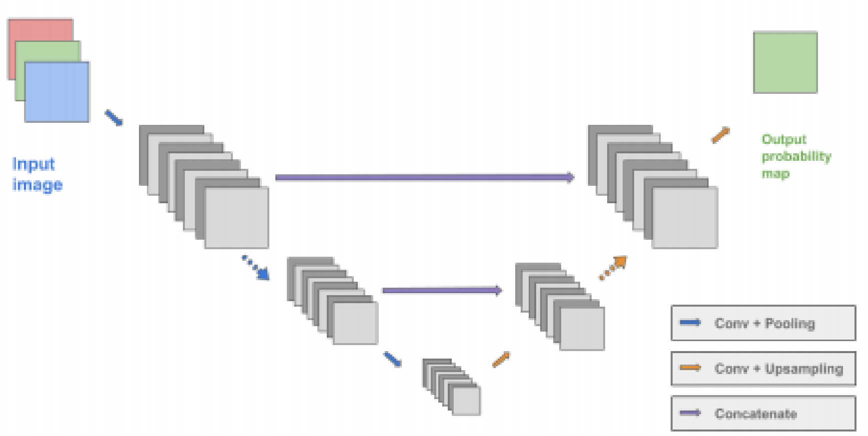


Figure 2. *FCA Architecture*

3.3. Contrast Limited Adaptive Histogram Equalization (CLAHE)

In histogram equalization, which is frequently used in image enhancement, image quality can be improved by expanding the density dynamic range with the entire image histogram. In histogram equalization, the intensity distribution of the image is normalized to obtain the result image with a uniform intensity distribution, and thus the improvement process is performed.

However, since histogram equalization uses the density distribution of the entire image, this can cause a faded effect on some images when the average intensity is set to medium. And in images with a crowded density distribution in a narrow region, it can cause many noise pixels to occur. Local histogram equalization techniques have been developed to solve these problems [18].

Adaptive histogram equalization is a modified histogram equalization operation and performs optimization on local data. The main idea here is that the image is divided into rectangular regions in the form of a grid and standard histogram equalization is applied to each region. Optimal region sizes and number vary depending on the image.

After the image is divided into sub-regions and histogram equalization is applied to each region, the sub-regions are combined with the bi-linear interpolation method to obtain an improved whole image [19]. However, the noise problem arose in adaptive histogram equalization. To prevent this, it is necessary to limit contrast enhancement in homogeneous regions, and for this purpose, the contrast limited adaptive histogram equalization (CLAHE) method has been developed.

The image is divided into small blocks called tiles. AHE equalizes the histogram for each tile as well. If there is some noise on the floor, the AHE amplifies the noise. Therefore, contrast limitation is used to avoid this problem. If there are any histogram splits above the contrast limit, these pixels are cut and evenly distributed. After equalization, linear interpolation is applied to correct the artificiality of the tile borders. With the CLAHE method, it can improve contrast in medical images, foggy images, underwater images, satellite images and natural images without increasing the effect of noise.

4. Discussion and Results

The manual process of histopathological analysis is laborious, time-consuming, and limited by the quality of the specimen and the experience of the pathologist. Exactly for this reason, the aim of the thesis will be to carry out this process in a computer environment, and an important step will be taken to eliminate the different decisions both in terms of time and between pathologists.

The dataset to be used in this study will be studied on the early diagnosis of Paratuberculosis (pTB) disease that has no treatment/vaccine, which is frequently seen in cattle / small cattle in the Burdur region.

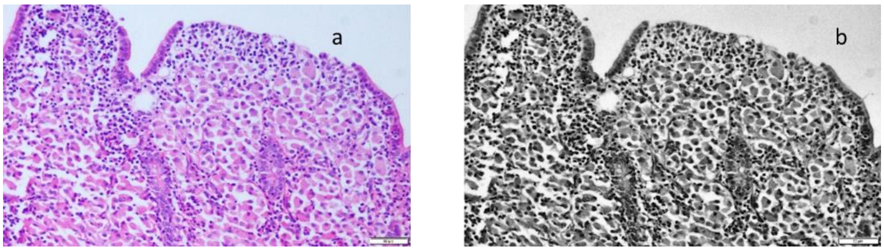


Figure 3. *a) Paratuberculosis image b) after data preprocessing with CLAHE*

In this study, the Fastai library was used. Fastai is a deep learning library built on PyTorch, developed to simplify the deep neural networks training process using cutting-edge deep learning approaches in various fields (e.g. computer vision, natural language processing, etc.).

Fastai is a modern deep learning library built on two main designs. It turns out to be a deeply configurable library as well as being accessible and fast productive. This library preserves both the clarity and development speed of the Keras library and the customization ability of the Pytorch library.

Recommended Fastai/VGG16 Model; It is a simple network model and the most important difference from the previous models is the use of convolution layers in 2 or 3 layers. It is converted into a feature vector with 7x7x512=4096 neurons in the full link (FC) layer. The 1000 class softmax performance is calculated at the output of the two fully connected layers. Approximately 140 million parameter calculations are made. As in other models, while the height and width dimensions of the matrices decrease from the input to the output, the depth value (number of channels) increases. At each convolution layer output of the model, filters with different weights are calculated, and as the number of layers increases, the features formed in the filters represent the 'depths' of the image.

The major contribution of the proposed Fastai/VGG-16 network shows that the depth of the network is a critical component for good performance. In this architecture, from the beginning to the end, only the 2x2 size filter is used in the convolution process, while keeping the network simple and protected in depth.

Although the network's biggest drawback was that it needed a lot of memory and parameters (approximately 140 million) when it was first proposed, it has been determined by the study that most of these parameters are in the first fully connected layer and removing this layer does not decrease the performance of the network much.

In this study, the effect of CLAHE method, which is one of the data preprocessing techniques, on histopathology images using deep learning was investigated. Metrics in the classification made on the data set without and using the CLAHE method; Classification Accuracy, Sensitivity, Specificity, Precision and F1 Scoring were performed. Fastai/VGG16 values without using the CLAHE method; shown in the table1below.

Table 1. *Performance Metrics (without CLAHE Method)*

Confusion Matrix Results VGG16		Classification Accuracy	Sensitivity	Specificity	Precision	F1 SCORE
TP	40	0,933333333	0,952381	0,9166667	0,909091	0,9302326
TN	44					
FP	4					
FN	2					

Values using Fastai/VGG16 with CLAHE method; shown in table 2.

Table 2. *Performance Metrics of Proposed Model Fastai/VGG16 (with CLAHE Method)*

Confusion Matrix Results VGG16		Classification Accuracy	Sensitivity	Specificity	Precision	F1 SCORE
TP	90	0,983606557	0,97826087	0,989011	0,989011	0,9836066
TN	90					
FP	1					
FN	2					

5. Conclusions and Future Work

As a result of the study, in this context; the use of deep learning systems for pathological diagnosis is a very new technique. However, it is rapidly becoming widespread due to the high rate of accurate and rapid diagnosis. This study showed that deep learning can be used to diagnose paratuberculosis.

In this study, a diagnosis and classification method was developed for paratuberculosis disease, which affects both animals and humans, using a new and original data set.

The data set of this study is expected to set an example for those working on disease classification and diagnosis. The data set to be shared with the employees on this subject may allow the development of different models.

Declaration of interest

It was presented at the ICAIAME 2021 conference and published as a summary.

References

[1] V. Santhi, D. P. Acharjya, M. Ezhilarasan, 2016, Biomedical Imaging Techniques, Book: Emerging Technologies in Intelligent Applications for Image and Video Processing, , https://doi.org/10.4018/978-1-4666-9685-3.ch016

[2] Garcia, A.B., Shalloo, L., 2015. Invited review: The economic impact and control of paratuberculosis in cattle. J. Dairy Sci. 98, 5019–5039. https://doi.org/10.3168/jds.2014-9241

[3] Wolf, R., Barkema, H.W., De Buck, J., Slomp, M., Flaig, J., Haupstein, D., Pickel, C., Orsel, K., 2014. High herd-level prevalence of Mycobacterium avium subspecies paratuberculosis in Western Canadian dairy farms, based on environmental sampling. J. Dairy Sci. 97, 6250–6259. https://doi.org/10.3168/jds.2014-8101

[4] Dufour, B., Pouillot, R., Durand, B., 2004. A cost/benefit study of paratuberculosis certification in French cattle herds. Vet. Res. 35, 69–81. https://doi.org/10.1051/vetres:2003045

[5] Cocito, C., Gilot, P., Coene, M. andKesel, M. 1994 'Paratuberculosis', Clinical Microbiology,Vol. 7,No. 3, pp.328–345.

[6] Whittington, R., Donat, K., Weber, M.F., Kelton, D., Nielsen, S.S., et al., 2019. Control of paratuberculosis: who, why and how. A review of 48 countries. BMC Vet. Res. 15, 198. https://doi.org/10.1186/s12917-019-1943-4

[7] Feller, M., Huwiler, K., Stephan, R., Altpeter, E., Shang, A., Furrer, H., Pfyffer, G.E., Jemmi, T., Baumgartner, A., Egger, M., 2007. Mycobacterium avium subspecies paratuberculosis and Crohn's disease: a systematic review and meta-analysis. Lancet Infect. Dis. 7, 607–613. https://doi.org/10.1016/S1473-3099(07)70211-6

[8] OIE (Office International des Epizooties), 2019. Paratuberculosis (accessed 19 December 2019).

https://www.oie.int/en/animal-health-in-the-world/animal-diseases/Paratuberculosis/

[9] Özturk D, Pehlivanoğlu F, Tok AA, Gunlu S, Guldali Y, Turutoglu H., Seroprevalence of paratuberculosis in the Burdur province (Turkey), in dairy cattle using the enzyme linked immunosorbent assay (ELISA). Israel J Vet Med, 65, 53-57

[10] Alom, M.Z.; Taha, T.M.; Yakopcic, C.; Westberg, S.; Sidike, P.; Nasrin, M.S.; Hasan, M.; Van Essen, B.C.; Awwal, A.A.; Asari, V.K. A state-of-the-art survey on deep learning theory and architectures. Electronics 2019, 8, 292

[11] M. D. Zeiler and R. Fergus, "Visualizing and understanding convolutional networks," in European Conference on Computer Vision, pp. 818–833, Springer, 2014.

[12] Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in Advances in Neural Information Processing Systems, pp. 1097–1105, 2012

[13] K. Simonyan and A. Zisserman, "Very deep convolutional networks for largescale image recognition," arXiv preprint arXiv:1409.1556, 2014

[14] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1–9, 2015

[15] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 580– 587, 2014

[16] Y. Gao, W. Rong, Y. Shen, and Z. Xiong, "Convolutional neural network based sentiment analysis using adaboost combination," in Neural Networks (IJCNN), 2016 International Joint Conference on, pp. 1333–1338, IEEE, 2016

[17] J. Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3431–3440, 2015

[18] Yoon H, Han Y, and Hahn H. Image Contrast Enhancement based Sub-histogram Equalization Technique without Over-equalization Noise. International Journal of Computer Science and Engineering 2009 : 3 (2)

[19] Teo CK. Digital Enhancement of Night Vision and Thermal Images. Thesis, Naval Postgraduate School, California, 2003

Advances in Artificial Intelligence Research (AAIR)
ISSN 2757-7422
www.dergipark.com/aair/

Vol. 2 (No. 1), pp. 7-14, 2022
doi: 10.54569/aair.1018444
Published online: Feb 16, 2022

Classification of Iris Flower by Random Forest Algorithm

Hilmi Cenk Bayrakçı [1,*], Abdullah Burak Keşkekçi [2], Recep Arslan [3]

[1] Isparta University of Applied Sciences, Dept. of Mechatronics Engineering, Isparta, Turkey;
[2] Isparta University of Applied Sciences, Dept. of Mechatronics Engineering, Isparta
[3] Isparta University of Applied Sciences, Dept. of Mechatronics Engineering, Isparta, Turkey;

Abstract

With the introduction of artificial intelligence into our lives, artificial intelligence researches and applications in different fields such as agriculture, health, military and engineering applications have become very popular iris flower was classified using the popular Random Forest, support vector machine and Artificial neural network machine learning classifiers with high accuracy rates. As a result of the classification, the performance of the trained models was evaluated according to the confusion matrix, sensitivity, specificity, accuracy, F1 score, ROC curve and AUC evaluation criteria. The random forest algorithm was the most successful among the trained algorithms with an accuracy rate of 97%.

Keywords: *Random Forest; iris dataset; classification*.

1. Introduction

Today, with the rapid development of technology, artificial intelligence methods are used in many areas. Artificial intelligence is a method that can model human thought and decision-making ability [1]. Artificial intelligence is a set of software and hardware systems that imitate human intelligence, can reason, and can make decisions in line with the experiences gained [2-4]. One of the frequently used branches of artificial intelligence is machine learning. Machine learning is fed from different sciences such as computer sciences, statistics and engineering. machine-learning; It performs different tasks such as classification, clustering, regression, pattern recognition, density estimation, outlier detection and information extraction [5]. Machine learning tasks are divided into two main headings, supervised learning and unsupervised learning [6]. While input and output sets are given in supervised learning, it is a learning method without output sets in unsupervised learning. For example, classification and regression operations are examples of supervised learning, while clustering and density are examples of unsupervised learning [7].

In this study, classification of the iris dataset was performed by using Random Forest (RF) machine learning classifier, which is fast, frequently used and has high accuracy [8]. At the end of the training, the performance of the model was evaluated according to the confusion matrix, sensitivity, originality, accuracy and F1 score evaluation criteria.

2. Material and Method

The iris data set was used in the study. For this data set, the data set was modelled using the RF algorithm with a software prepared in the Python programming language.

2.1. Material

Materials such as iris data set, RF algorithm and performance evaluation criteria used in the material part of the study will be given as sub-titles based on both in-formation and literature.

2.1.1. Iris Dataset

The iris data set used in the study consists of three different classes, setose, versicolor and virginica, and 150 rows and 4 columns. There are 50 different examples for each class. In the study, it was tried to model with RF algorithm using these data. In Table 1, the characteristics and statistical information of the iris data set are given.

*Corresponding author
E-mail address: cenkbayrakci@isparta.edu.tr
Received: 04/Nov/2021; Received in revised form: 04/Jan/2022; Accepted: 17/04/2022.

Table 1. *Characteristics and statistical information of the Data Set*

Feature	Meaning	Range	Average
sepal length	Lower leaf length	4.3-7.9	5.843
sepal width	Lower leaf width	2.0-4.40	3.057
petal length	Upper leaf length	1.0-6.9	3.758
petal width	Upper leaf width	0.1-2.5	1.199

2.1.2. RF Algorithm

RF is a community machine learning algorithm developed by Leo Breiman [9]. Ensemble classification algorithms contain multiple classifiers instead of a single classifier [10]. The structure of the RF algorithm includes more than one decision tree, it gives results by taking the average of the decision trees [11]. A trained k-number trees are collected in an RF model defined in Equation 1 [12].

$$H(X, \theta_j) = \sum_{i=0}^{k} h_i(x, \theta_j) \quad ,(j = 1,2,3, \dots, m) \tag{1}$$

In the equation, H (X, θ_j) is a meta decision tree classifier. x represents the input feature vector of the training dataset and θ_j is an independent and uniformly distributed random vector that determines the growth process of the tree [1].

2.1.3. Support Vector Machine Algorithm

Today, Support Vector machines (SVM) are a widely used method in many fields such as engineering, healthcare and agriculture [13]. SVM is divided into two main classes, Support Vector Classification (SVC) and Support Vector Regression (SVR) [14]. SVR is generally used in measurable learning and nonlinear regression Using Equation 2, the most accurate function is found with SVR in the hypothesis function set. In the equation, x represents the training data set, w represents the weight vector and b represents the threshold value [14].

$$\{f \mid f(x) = w^T x + b, \ w \in \mathbb{R}^d, \ b \in \mathbb{R}\} \tag{2}$$

2.1.4. Artificial Neural Networks (ANN)

Artificial neural networks (ANN), one of the artificial intelligence methods, have been used quite frequently in recent years [15]. ANN expresses a mathematical model that is structurally similar to biological neurons [16]. ANN is a method of estimating an output sequence from input variables entered as a sequence as a mathematical model [17]. ANNR is a model that shows a nonlinear match between an input vector and an output vector, as seen in Figure 1. The i_1, i_2 and i_3 in the figure represent the input vectors, and the O_1 and O_2 values represent the output vectors [18].

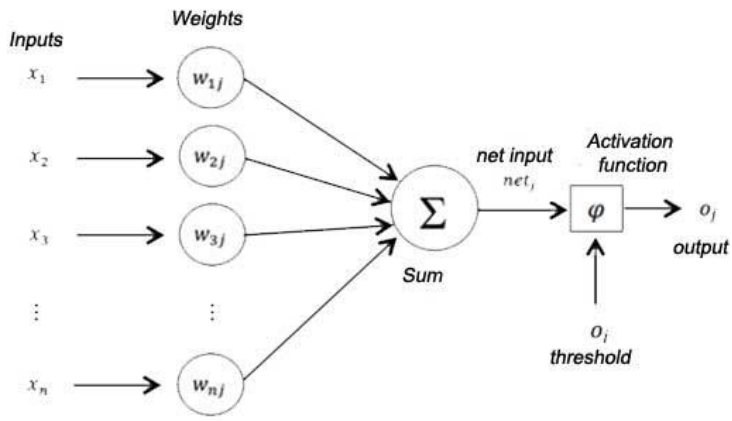


Figure 1. *Structure of ANN [18]*

2.1.5. Performance Evaluation Criteria

All Different evaluation criteria such as Receiver Operating Area Under the ROC Curve (AUC), Characteristic Curve (ROC), sensitivity, authenticity, accuracy and F1 score are frequently used in classification processes. The ROC curve is a probability curve for different classes. In the ROC curve, False

Positive Rate (FPR) values on the horizontal axis and True Positive Rate (TPR) values on the vertical axis are used. The AUC value is the area under the ROC curve. Equations for sensitivity, Specificity, accuracy and F1 score are given in 2-5 [18-23].

$$Sensitivity = \frac{TP}{TP+FN} \tag{2}$$

$$Specificity = \frac{TN}{TN+FP} \tag{3}$$

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \tag{4}$$

$$F1\ Score = \frac{2*TP}{2*TP+FN+FP} \tag{5}$$

2.2. Method

In the study, the workflow diagram of the classification of iris flower with random forest is given in figure 2. First, the open access iris dataset was taken. In the second stage, the data set was divided into two as training 80% and test 20%. During the training phase, three different artificial intelligence algorithms, namely RF, SVM and ANN, were trained. The number of estimators was set to 80 and maximum depth 10 without final training in the RF algorithm. In the SVM algorithm, the thickness of tube (ε) was chosen as 1.4, the penalty factor (C) was 25 and the kernel coefficient values (γ) was 0.000125. The ANN model created in the study includes a single hidden layer. 20 neurons and relu activation functions were used in the hidden layer. An ANN model with four inputs and three outputs, sepal length, sepal width, petal length and petal width, is designed. In the training process of the ANN model, the value of the batch size is 10, the number of epoch is 50 and the optimization method is man. The final models to be obtained after the training process was completed were tested on the test data set. In the last stage, the trained model-in test data set was evaluated according to the confusion matrix, sensitivity, specificity, accuracy and F1 score, ROC and AUC evaluation criteria.

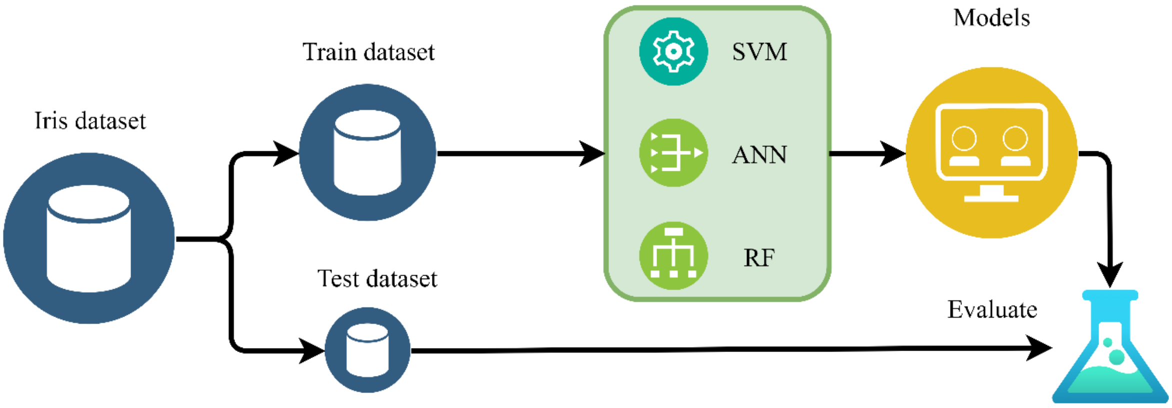


Figure 2. *Workflow diagram*

3. Research Findings and Discussion

In the study, classification process was carried out on the iris dataset consisting of 150 different samples and containing iris flower information with the random forest, support vector machine and artificial neural networks machine learning algorithm using the Python programming language. As a result of training random forest important measurements were made on 3 attributes. The graph of the importance of the attributes is shown in Figure 3.

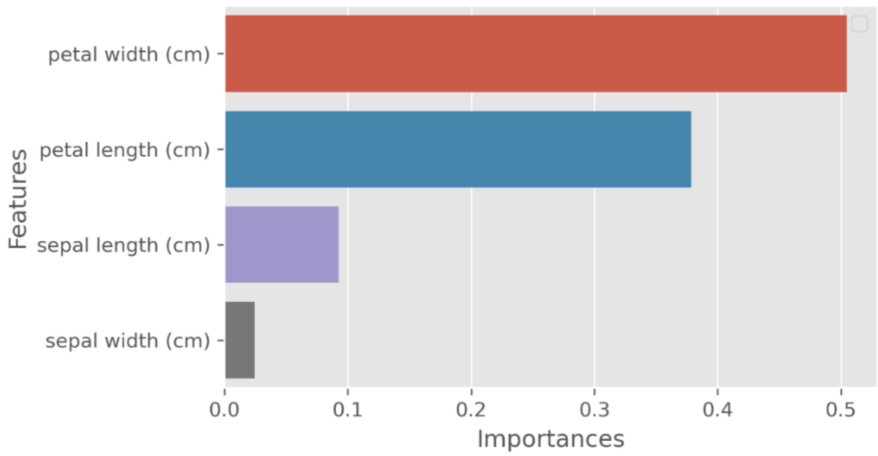


Figure 3. *Significance graph of attributes*

When Figure 3 is examined, it is seen that the "petal length" attribute has the most effect on the trained model and is the most important parameter. The "sepal width" attribute is the least important attribute. The trained model of RF was tested with 30 data. The confusion matrix of RF formed after the test and estimation process is given in figure 4.

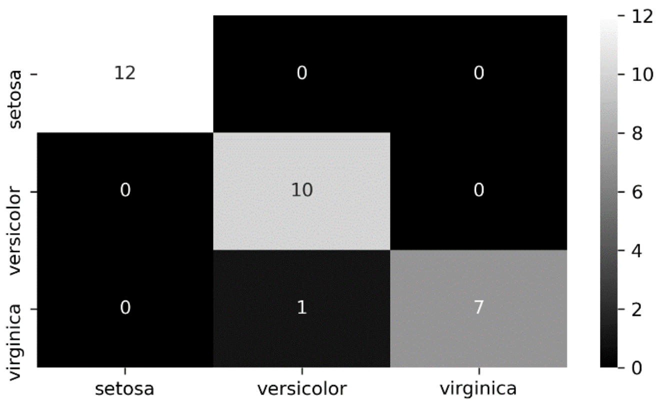


Figure 4. *Confusion Matrix of RF*

When the confusion matrix given in Figure 4 is examined, the number of correctly and incorrectly estimated by RF samples belonging to three different classes is seen. As shown in the confusion matrix, 29 out of 30 data were predicted correctly. It is seen that the model obtained in this way correctly detects the classes with an accuracy of approximately 97%. Since the data set used in the modelling includes more than two classes, the macro calculation method, which is one of the multi-class evaluation techniques, was preferred. Evaluation results are given in Table 2. When Table 2 is examined, it is seen that the model obtained is quite successful. The accuracy of the trained model was determined as 97%.

Table 2. *evaluation results of RF*

Evaluation Criteria	Value
Sensitivity	0.96
Specificity	0.97
F1 score	0.97
AUC	0.97
Accuracy	0.97

As seen in Table 2, the AUC value was obtained as 0.97. It has been observed that the AUC value is almost close to 1. The ROC curve is given in figure 4 to examine the accuracy of the model graphically. When examined in Figure 4, the ROC curve of each class is given and the AUC values are shown. When the curve is examined, it is seen that it gives a result close to an ideal ROC curve in the detection of iris flower.

Figure 4. *ROC curve and AUC values of RF*

After training RF model to compare it with other machine learning model we tried SVM and ANN models. The trained SVM model was tested with 30 data. The confusion matrix of SVM formed after the test and estimation process is given in figure 5.

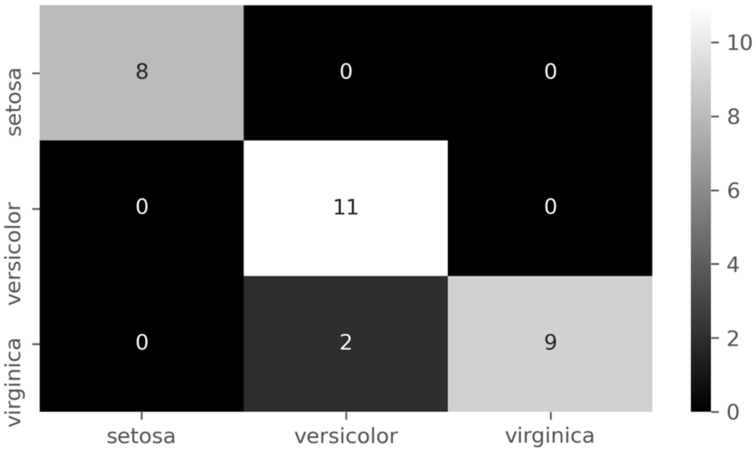


Figure 5. *Confusion Matrix of SVM*

When the confusion matrix of SVM given in Figure 5 is examined, the number of correctly and incorrectly estimated samples belonging to three different classes is seen. As shown in the confusion matrix, 29 out of 30 data were predicted correctly. It is seen that the model obtained in this way correctly detects the classes with an accuracy of approximately 93%. Since the data set used in the modelling includes more than two classes, the macro calculation method, which is one of the multi-class evaluation techniques, was preferred. Evaluation results are given in Table 3. When Table 3 is examined, it is seen that the model obtained is quite successful. The accuracy of the trained model was determined as 93%.

Table 3. *evaluation results of SVM*

Evaluation Criteria	Value
Sensitivity	0.94
Specificity	0.95
F1 score	0.93
AUC	0.95
Accuracy	0.93

As seen in Table 3, the AUC value was obtained as 0.95. It has been observed that the AUC value is almost close to 1. The ROC curve is given in figure 6 to examine the accuracy of the model graphically. When examined in Figure 6, the ROC curve of each class is given and the AUC values are shown. When the curve is examined, it is seen that it gives a result close to an ideal ROC curve in the detection of iris flower.

Figure 6. *ROC curve and AUC values of SVM*

After training RF model to compare it with other machine learning model we tried SVM and ANN models. The trained ANN model was tested with 30 data. The confusion matrix of ANN formed after the test and estimation process is given in figure 7.

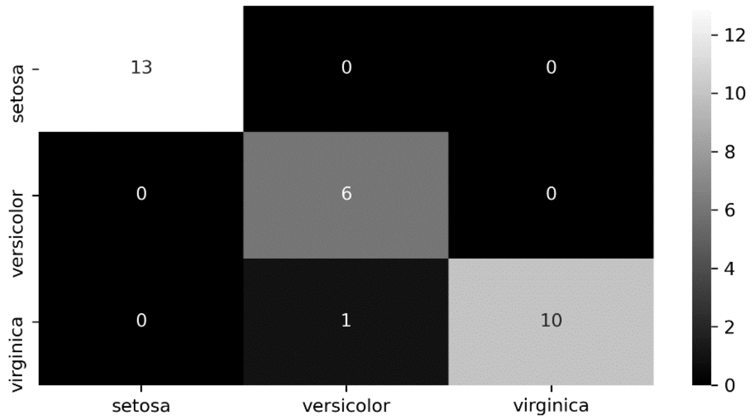


Figure 7. *Confusion Matrix of ANN*

When the confusion matrix of ANN given in Figure 7 is examined, the number of correctly and incorrectly estimated samples belonging to three different classes is seen. As shown in the confusion matrix, 29 out of 30 data were predicted correctly. It is seen that the model obtained in this way correctly detects the classes with an accuracy of approximately 97%. Since the data set used in the modelling includes more than two classes, the macro calculation method, which is one of the multi-class evaluation techniques, was preferred. Evaluation results are given in Table 4. When Table 4 is examined, it is seen that the model obtained is quite successful. The accuracy of the trained model was determined as 97%.

Table 4. *evaluation results of ANN*

Evaluation Criteria	Value
Sensitivity	0.97
Specificity	0.95
F1 score	0.96
AUC	0.95
Accuracy	0.97

As seen in Table 4, the AUC value was obtained as 0.97. It has been observed that the AUC value is almost close to 1. The ROC curve is given in figure 8 to examine the accuracy of the model graphically. When examined in Figure 8, the ROC curve of each class is given and the AUC values are shown. When the curve is examined, it is seen that it gives a result close to an ideal ROC curve in the detection of iris flower.

Figure 8. *ROC curve and AUC values of ANN*

3. Conclusion

AI methods are frequently used in agriculture, as in many different fields, like early detection of many plant diseases and plays an important role in determining whether the plants are suitable for harvesting. In the study, the type of iris flower was determined with a random forest, support vector machine and artificial neural networks algorithms and the classification accuracy was evaluated in terms of performance. Obtained performance results are given below.

- The confusion matrix is obtained for the random forest classifier. It was observed that only 1 out of 30 samples was detected incorrectly in the confusion matrix.
- The trained model by random forest was found to be successful with 97% accuracy, 97% specificity, 96% sensitivity, 97% F-measure and 97% AUC value.
- The confusion matrix is obtained for the support vector machine classifier. It was observed that only 2 out of 30 samples was detected incorrectly in the confusion matrix.
- The trained model by support vector machine was found to be successful with 93% accuracy, 95% specificity, 94% sensitivity, 93% F-measure and 95% AUC value.
- The confusion matrix is obtained for the artificial neural networks. It was observed that only 1 out of 30 samples was detected incorrectly in the confusion matrix.
- The trained model by random forest was found to be successful with 97% accuracy, 95% specificity, 97% sensitivity, 96% F-measure and 95% AUC value.

With the results obtained in the study, an artificial intelligence-based model has been proposed for the classification of iris flower. With this proposed model, it is aimed to contribute to the academic literature for the applications of artificial intelligence in the field of agriculture. In future academic studies, it is thought to increase the accuracy rate by using different artificial intelligence models.

Declaration of interest

It was presented as a summary at the ICAIAME 2021 conference.

References

[1] Özkan, İ. N. İ. K., & Ülker, E. (2017). Derin Öğrenme ve Görüntü Analizinde Kullanılan Derin Öğrenme Modelleri. Gaziosmanpaşa Bilimsel Araştırma Dergisi, 6(3), 85-104.

[2] Russell SJ, Norvig P. Artificial intelligence: a modern approach. 3rd ed. Pearson Education Inc:New Jersey;2016.

[3] Jiang F, Jiang Y, Zhi H, Dong Y, Li H, Ma S, et al. Artificial intelligence in healthcare: past, present and future. Stroke and Vascular Neurology. 2017;2(4):230-243.

[4] Aksoy, B, Halis, H, Salman, O. (2020). Elma Bitkisindeki Hastalıkların Yapay Zekâ Yöntemleri ile Tespiti ve Yapay Zekâ Yöntemlerinin Performanslarının Karşılaştırılması. International Journal of Engineering and Innovative Research, 2 (3), 194-210. DOI: 10.47933/ijeir.772514

[5] Mitchell T. Machine Learning. New York, USA, McGraw Hill, 1997.

[6] Kalaycı, T. E. (2018). Kimlik hırsızı web sitelerinin sınıflandırılması için makine öğrenmesi yöntemlerinin karşılaştırılması. Pamukkale Üniversitesi Mühendislik Bilimleri Dergisi, 24(5), 870-878.

[7] Harrington P. Machine Learning in Action. New York, USA, Manning Publications, 2012.

[8] Osisanwo, F. Y., Akinsola, J. E. T., Awodele, O., Hinmikaiye, J. O., Olakanmi, O., & Akinjobi, J. (2017). Supervised machine learning algorithms: classification and comparison. International Journal of Computer Trends and Technology (IJCTT), 48(3), 128-138.

[9] Breiman, L. Rastgele Ormanlar. Machine Learning 45, 5-32 (2001).

[10] Akar, Ö., & Güngör, O. (2012). Rastgele orman algoritması kullanılarak çok bantlı görüntülerin sınıflandırılması. Jeodezi ve Jeoinformasyon Dergisi, ss, 139-146.

[11] Korkmaz, D., Çelik, H. E., & Kapar, M. Sınıflandırma ve Regresyon Ağaçları ile Rastgele Orman Algoritması Kullanarak Botnet Tespiti: Van Yüzüncü Yıl Üniversitesi Örneği. Yüzüncü Yıl Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 23(3), 297-307.

[12] Chen, J., Li, K., Tang, Z., Bilal, K., Yu, S., Weng, C., & Li, K. (2016). A parallel random forest algorithm for big data in a spark cloud computing environment. IEEE Transactions on Parallel and Distributed Systems, 28(4), 919-933.

[13] Mohammadi, K., Shamshirband, S., Anisi, M. H., Alam, K. A., & Petković, D. (2015). Support vector regression based prediction of global solar radiation on a horizontal surface. Energy Conversion and Management, 91, 433-441.

[14] Zhang, L., Zhou, W. D., Chang, P. C., Yang, J. W., & Li, F. Z. (2013). Iterated time series prediction with multiple support vector regression models. Neurocomputing, 99, 411-422.

[15] Yang, Z., Cai, Y., Li, Q., Li, H., Jiang, Y., Lin, R., ... & Gao, X. (2021). Predicting particle collection performance of a wet electrostatic precipitator under varied conditions with artificial neural networks. Powder Technology, 377, 632-639.

[16] Taşar, B., Üneş, F., Demirci, M., & Kaya, Y. Z. (2018). Yapay sinir ağları yöntemi kullanılarak buharlaşma miktarı tahmini. DÜMF Mühendislik Dergisi, 9(1), 543-551.

[17] Taşar, B., Üneş, F., Demirci, M., & Kaya, Y. Z. (2018). Yapay sinir ağları yöntemi kullanılarak buharlaşma miktarı tahmini. DÜMF Mühendislik Dergisi, 9(1), 543-551.

[18] Budak, H., & Erpolat, S. (2012). Kredi Riski Tahmininde Yapay Sinir Ağları ve Lojistik Regresyon Analizi Karşılaştırılması. AJIT-e: Online Academic Journal of Information Technology, 3(9), 23-30.

[19] Zhu, W., Zeng, N., & Wang, N. (2010). Sensitivity, specificity, accuracy, associated confidence interval and ROC analysis with practical SAS implementations. NESUG proceedings: health care and life sciences, Baltimore, Maryland, 19, 67.

[20] Lalkhen, A. G., & McCluskey, A. (2008). Clinical tests: sensitivity and specificity. Continuing Education in Anaesthesia Critical Care & Pain, 8(6), 221-223.

[21] Eusebi, P. (2013). Diagnostic accuracy measures. Cerebrovascular Diseases, 36(4), 267-272.

[22] Chicco, D., & Jurman, G. (2020). The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. BMC genomics, 21(1), 6.

[23] Ekrem, Ö., Salman, O. K. M., Aksoy, B., & İnan, S. A. (2020). Yapay Zekâ Yöntemleri Kullanilarak Kalp Hastaliğinin Tespiti. Mühendislik Bilimleri ve Tasarım Dergisi, 8(5), 241-254.

Advances in Artificial Intelligence Research (AAIR)
ISSN 2757-7422
www.dergipark.com/aair/

Vol. 2 (No. 1), pp. 15-19, 2022
doi: 10.54569/aair.1029836
Published online: Feb 16, 2022

SALDA-ML: Machine Learning Based System Design to Predict Salary Increase

Yasin Görmez [1,*], Halil Arslan [2], Suat Sarı [3], Mücahit Danış [3]

[1] Sivas Cumhuriyet University, Management Information Systems, Sivas, Turkey
[2] Sivas Cumhuriyet University, Computer Engineering, Sivas, Turkey
[3] Detaysoft, İstanbul, Turkey

Abstract

Number of employees are increases with growing in companies. Firms basically make salary increases for their employees in order not to lose their talents and moreover to increase them. Although there is not much problem in how to in-crease the salary in small organizations, this process should be carried out carefully in terms of many parameters in large organizations and should not result in negativities that may disrupt employee motivation. For companies with a large number of employees, creating a model in which the market conditions are determined correctly and all economic parameters are taken into account reveals the need for a process that needs to be worked on for months. In this context, a machine learning-based salary increase prediction system was designed with the study. Specific attributes were determined and a specific scale was developed for performance score for this study.

Keywords: *Salary Increase, Machine Learning, Work Flow, Personnel Performance Measurement, System Design, Software Develop*

1. Introduction

There is an increase in the human resources with the growth of companies. Personnel management and keeping personnel motivation high are very important for these companies to execute their business process properly. According to the research, one of the important factors affecting the high motivation is that the personnel think they are getting the salary they deserve [1]. Salaries in companies in Turkey are usually determined annually. Determining the most appropriate salary increase every year is one of the important issues for these companies. Methods such as collective agreement, opinion of the person manager, and increase according to the rate determined by the governments due to inflation can be preferred in salary increase. However, none of these methods is sufficient on its own to determine proper salary for employees. According to the research many factors, which also include gender, effect the salary increase [2]. One of the most important problems of collective bargaining or inflationary salary increase methods is that the personnel who do more work and those who do less work cannot be distinguished. It has been observed that, personnel with a high capacity in the companies that applied these methods for a long time lost their motivation over time. Therefore, they started to do less work or changed jobs [3]. In addition, inflation and living conditions in a country may differ for each region. When all these cases are examined, it is clear that salary increase is a problem that does not have a linear solution depending on many factors.

Within the scope of the study, it is aimed to design a system based on machine learning that can predict personnel salary increase. During the system design phase, the experience of our company, which has been doing business with holding-level institutions around the world for more than 20 years, was utilized. In this context, taking into account our previous studies, it is aimed to use the inflation rate in the country, the inflation rate in the region, regional information, personnel level, exchange rate information, company policy, business area multiplier and performance score as attributes for the machine learning model. Data from consulting firms such as Korn Ferry (Hay Group) that collected market analysis data as a result of surveys were used to create these features [4]. The performance score is an indicator that represents the efficiency of the personnel during the year. A novel scale was developed to calculate this score that specific to this study. This performance measure will be calculated using data that are collected from enterprise resource planning (ERP) databases. In this context, a table will be designed in the ERP database that is compatible with personnel work tracking systems. Table fields are explained in detail in the following parts of the study. In addition, the system salary increase rate also differs on the basis of the sector [5]. Therefore, this system will be developed using micro-service architecture to make it modularize it. In this way, different machine learning model can be developed for different companies. If a new company wants to use the system, a company-specific model will be trained using the historical data of that company. Virtualization will be used to provide all of these attributes. In addition to all of these, system will be improved with correction by taking opinion of the experts.

*Corresponding author
E-mail address: yasingormez@cumhuriyet.edu.tr

Received: 29/Nov/2022; Received in revised form: 07/Jan/2022; Accepted: 21/Jan/2022.

2. Literature Review

Various studies have been conducted in the literature on the effects of salary on individuals. Kathawala et al. conducted a study on the preference for increased salary or job security for automotive industry workers. As a result of the research, it has been determined that white-collar personnel prefer salary increase rather than job security and personnel who prefer salary increase are less satisfied with their salary [6]. Mohan and Muthuswamy showed that people tend to leave their jobs in organizations with insufficient salary increase or no promotional payments [7]. Indrasari et al. Indrasari et al. analyzed the relationship between salary satisfaction, job satisfaction and organizational commitment. They concluded that job satisfaction has a positive effect on organizational commitment, while job satisfaction, salary satisfaction and organizational commitment have a negative effect on quitting [8].

In addition to these studies, several machine learning models developed to predict salary increase. Khongchai and Songmuang compared k-nearest neighbor (k-nn), naïve Bayes (NB), decision trees (DT), artificial neural networks (ANN) and support vector machines (SVM) to measure of their performance on estimating salary of students after graduation. According to results 84.69%, 43.63%, 73.96%, 38.08%, 43.71% accuracies were obtained with k-nn, NB, J48 DT, ANN and SVM respectively [9]. Wang et al. developed a machine learning system using bi-directional long short-term memories (bi-LSTM) and convolutional neural networks (CNN) to predict salary on dataset that generated using job search engine and they obtained better results than the literature [10]. Martin et al. analyzed machine learning methods to predict salary of employees that works in the field of information technology in Spain and they showed that the best accuracy, which is 84%, was obtained with decision tree algorithm [11]. Bansal et al. compared simple linear regression and multiple linear regression to predict personnel salary and they showed that multiple linear regression was obtained better accuracy results [12]. Das et al designed a system to estimate personnel salary after specific time and they shared the visual results of that system [13]. Li et al. predict the salary of employees using support vector regression, nearest geometric center, linear regression, logistic regression, k nearest regression and random forest regression on dataset that generated using job posting in England and they obtained 0.184% mean absolute error [14]. Zhang and Cheng obtained 88.10% accuracy for salary range estimation with k-nn for Java back-end developer using knowledge in basic Java programming, database principle, Java web score, system programming and Linux course and education information [15]. Mobasshera et al. developed a system using adaptive network-based fuzzy inference to predict salary increase and they made estimates very close to the real increase [16]. Viroon-luecha and Kaewkiriya obtained 0.774 root mean square error with deep learning approach for estimation of monthly salary using job posting data in Thailand [17].

3. Proposed System

In this study, a system, which can work integrated with ERP system, was designed to predict salary increase that uses inflation rate in the country, inflation rate in the region, region information, personnel level, exchange rate information, company policy, business multiplier and performance score a feature. Firstly, a performance score should be calculated for this system. In order to calculate score, a job tracking table must first be created. The table can be created in the existing business tracking systems of the institutions or can be integrated into the existing business tracking systems when necessary. This table contains columns for job identifier number, estimated job duration (man-day), job value ratio, job assignment date, and job closure date. The job value ratio represents a real number between zero and one determined by the manager according to the difficulty of the assigned job. If this value is close to one, it means that the task is more difficult. The score calculation for each job assigned to the personnel will be calculated using the formula in equation 1, and the total score of the personnel will be calculated using the formula in equation 2.

$$ts_{ij} = \frac{\{(estimated\ work\ time \mid present\ day - job\ assigment\ date\ ) \times job\ value\ ratio\}}{total\ workers\ in\ assigment} \tag{1}$$

$$s_j = \sum_{i=1}^{N} ts_{ij} \tag{2}$$

In equation 1, while calculating $(estimated\ work\ time \mid present\ day - job\ assigment)$ part, the value will be $estimated\ work\ time$ if job is finished, and if not, the value will be $present\ day - job\ assigment$. For example if $estimated\ work\ time$ is 2 months and the starting date of job is first of January, $(estimated\ work\ time \mid present\ day - job\ assigment)$ part will be 30 where ts_{ij} calculated in first of February and it will be 60 where ts_{ij} calculated after first of March. Later on, calculated performance score will be used as a feature for proposed system. In the first example, if performance score calculated after March, job value ratio is 0.7 (difficulty level of the job) and 4 employees assigned for this job, ts_{ij} will be *(60 x 0.7) / 4 = 10.5*. This means a performance score for this job calculated for each employee in the job. Performance score of employees will be computed as sum of each performance score calculated from their tasks. Figure 1 shows the architecture of proposed system.

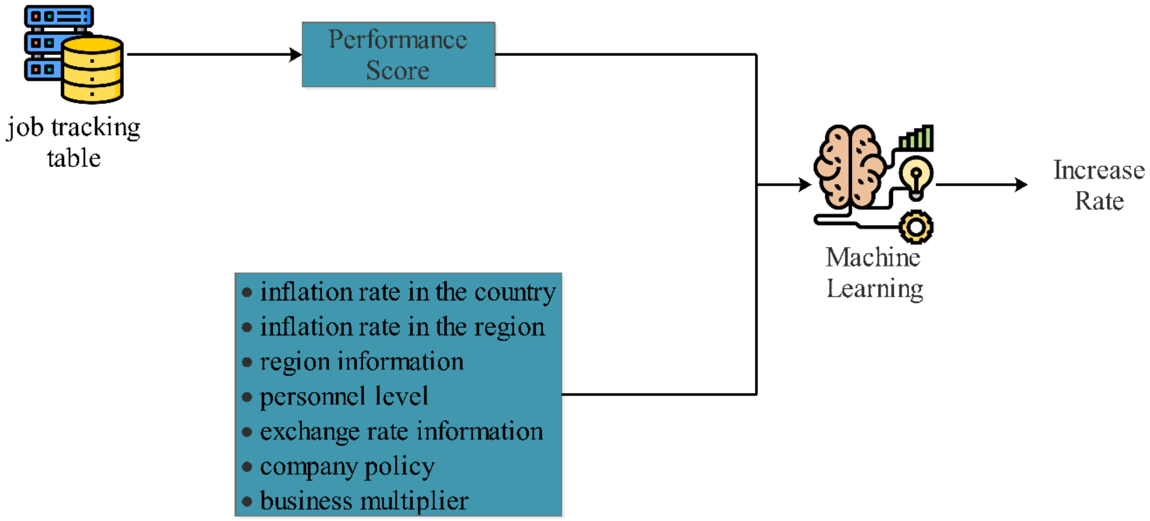


Figure 1. *Proposed System Architecture*

In figure 1, performance score represents value that calculated using equation 1 and equation 2. Remaining features will be taken from the database that integrated with ERP systems. Each attributes in this databases determined according to analysis and research [4]. Each field can be expressed in detail as:

- Inflation rate in the country: Inflation rate that covers the entire country, announced monthly or annually.
- Inflation rate in the region: Inflation rate in the province where the institution is located. This information was needed because the inflation in the region may differ from the inflation in the country.
- Region information: Information on the province where the institution is located. It is known that basic needs expenditures (food and beverage, transportation, rent, etc.) differ on a provincial basis and these expenditures have a direct related with salary. Therefore, this information is needed.
- Personnel Level: The position of the personnel is one of the most important factors affecting the salary increase. This effect becomes much more important especially in level changes. Considering the mentioned factors, it was concluded that this parameter value should be used in the model.
- Exchange rate information: Exchange rate information at the time of salary increase. Since exchange rate information is one of the important factors (especially for countries with a current account deficit) that determine the price of basic needs or secondary needs, it is considered to be in the model.
- Company policy: It represents a multiplier between 0 and 1 that the company has created for its own policies. For example, the company may want to raise more or less than inflation this year. If this multiplier is close to 1, it means that there will be more raises.
- Business multiplier: It represents the value between 0 and 1, which indicates the coefficient of the work area (information processing, human resources, etc.) in which the personnel works. If this number is close to 1, it represents a further increase in that area.

Considering the structure of the system and the number of parameters in the system, it is seen that there is a problem that cannot be solved linearly. Therefore, it is thought that, machine learning models, which were obtained accurate results in many field such as sentiment analysis [18] – [20], object recognition from image [21] – [23] and bioinformatics [24] – [26], can be used to predict salary increase with the least error. In this context, it’s aimed to use methods based on machine learning in the last stage of the proposed system. It is possible for different machine learning models to yield more successful results according to the data structure of each institution and the number of data collected. Before installation for the intuitions, linear regression, artificial neural networks, random forest regression and deep learning approaches will be analyzed to determine most suitable models for that intuition. Then, a final model will be trained using all the data in the institution and this model will be used as the decision maker of the system.

Considering today's technological level and fast living conditions, the needs of institutions can change very quickly. Micro-service architecture was used to design the system considering this situation. Each module in the system will be virtualized and the modules will be able to communicate with each other via service intermediary. In this way, it will be possible to add modules to the system in line with new requirements. In addition to all these, the developed machine learning model will be developed in structures that enable it to be developed with the online method, in line with expert opinions.

4. Conclusions

In the study, the relationship between the salary of the personnel and their motivation and productivity was analyzed with the literature review and salary prediction system in the literature was analyzed. As a result of these analysis, it has been concluded that the salary increase rate estimation can be made with machine learning methods. In this context, a salary increases estimation system based on machine learning, which can also be integrated into ERP systems, has been designed for institutions and organizations. The study specific features were determined and performance score were concatenated with these features. A study-specific scale was developed to calculate the performance score. In order to develop the designed system to meet future corporate needs, it is thought to use a microservice architecture. In addition, structures that allow the machine learning model to update itself in line with the needs have been designed.

In the future, it's aimed to install proposed system in to company from information technology sector for testing it. For this purpose, web services were developed according to features in this study to collect data from task tracking systems. In this way, the study-specific data will be collected. Therefore, contribution will be made the literature with this dataset. Machine learning model will be analyzed on this datasets and best accurate model will be determined. Then, the system will be installed in the relevant institution, and the operating performance of the system will be measured with real-time data, and system load tests will be carried out. For the mentioned reasons, it is thought that the system will be a study that will be open to development and will be the basis for machine learning-based systems.

Acknowledgment

This study is an output of studies conducted in DetaySoft research and development center. We appreciate their support.

Declaration of interest

It was presented as a summary at the ICAIAME 2021 conference.

References

[1] D. Card, A. Mas, E. Moretti, and E. Saez, 'Inequality at Work: The Effect of Peer Salaries on Job Satisfaction', Am. Econ. Rev., vol. 102, no. 6, pp. 2981–3003, Oct. 2012, doi: 10.1257/aer.102.6.2981.

[2] R. A. Thacker, 'Gender, influence tactics, and job characteristics prefer-ences: New insights into salary determination', Sex Roles, vol. 32, no. 9, pp. 617–638, May 1995, doi: 10.1007/BF01544215.

[3] J. R. Hill and N. A. Jolly, 'Salary Distribution and Collective Bargaining Agreements: A Case Study of the NBA', Ind. Relat. J. Econ. Soc., vol. 51, no. 2, pp. 342–363, 2012, doi: https://doi.org/10.1111/j.1468-232X.2012.00680.x.

[4] 'Korn Ferry | Organizational Consulting'. https://www.kornferry.com (ac-cessed Mar. 31, 2021).

[5] K. S. Koong, L. C. Liu, and R. Fowler, 'Salaries of information technology managers; A trend analysis', p. 15, 2003.

[6] Y. Kathawala, K. J. Moore, and D. Elmuti, 'Preference between Salary or Job Security Increase', Int. J. Manpow., vol. 11, no. 7, pp. 25–31, Jan. 1990, doi: 10.1108/01437729010004174.

[7] S. Mohan and P. R. Muthuswamy, 'A study on employee retention in BPO Sector with special reference to Coimbotore', Int. J. Inf. Futur. Res., vol. 2, no. 6, 2015.

[8] M. Indrasari, B. R. Purnomo, E. Yunus, E. Haryati, and A. R. Hashmi, 'The Effect of Salary Satisfaction, Work Satisfaction and Organizational Com-mitment To Work Intention', J. Didask., vol. 1, no. 1, Art. no. 1, Nov. 2018, doi: 10.33856/didaskalia.v1i1.54.

[9] P. Khongchai and P. Songmuang, 'Implement of salary prediction system to improve student motivation using data mining technique', in 2016 11th International Conference on Knowledge, Information and Creativity Sup-port Systems (KICSS), Nov. 2016, pp. 1–6. doi: 10.1109/KICSS.2016.7951419.

[10] Z. Wang, S. Sugaya, and D. P. T. Nguyen, 'Salary Prediction using Bidirec-tional-GRU-CNN Model', p. 4, 2019.

[11] I. Martín, A. Mariello, R. Battiti, and J. A. Hernández, 'Salary Prediction in the IT Job Market with Few High-Dimensional Samples: A Spanish Case Study', Int. J. Comput. Intell. Syst., vol. 11, no. 1, pp. 1192–1209, Jul. 2018, doi: 10.2991/ijcis.11.1.90.

[12] U. Bansal, A. Narang, A. Sachdeva, I. Kashyap, and S. P. Panda, 'Empirical analysis of regression techniques by house price and salary prediction', IOP Conf. Ser. Mater. Sci. Eng., vol. 1022, p. 012110, Jan. 2021, doi: 10.1088/1757-899X/1022/1/012110.

[13] S. Das, R. Barik, and A. Mukherjee, 'Salary Prediction Using Regression Techniques', Social Science Research

Network, Rochester, NY, SSRN Scholarly Paper ID 3526707, Jan. 2020. doi: 10.2139/ssrn.3526707.

[14] L. Li, X. Liu, and Y. Zhou, 'Prediction of Salary in UK', p. 5.

[15] J. Zhang and J. Cheng, 'Study of Employment Salary Forecast using KNN Algorithm', Aug. 2019, pp. 166–170. doi: 10.2991/msbda-19.2019.26.

[16] A. Mobasshera, K. Naher, T. M. Rezoan Tamal, and R. M. Rahman, 'Sala-ry Increment Model Based on Fuzzy Logic', in Artificial Intelligence and Algorithms in Intelligent Systems, Cham, 2019, pp. 344–353. doi: 10.1007/978-3-319-91189-2_34.

[17] P. Viroonluecha and T. Kaewkiriya, 'Salary Predictor System for Thailand Labour Workforce using Deep Learning', in 2018 18th International Sym-posium on Communications and Information Technologies (ISCIT), Sep. 2018, pp. 473–478. doi: 10.1109/ISCIT.2018.8587998.

[18] R. Chiong, Z. Fan, Z. Hu, M. T. P. Adam, B. Lutz, and D. Neumann, 'A Sen-timent Analysis-based Machine Learning Approach for Financial Market Prediction via News Disclosures', in Proceedings of the Genetic and Evolu-tionary Computation Conference Companion, New York, NY, USA, 2018, pp. 278–279. doi: 10.1145/3205651.3205682.

[19] Ankit and N. Saleena, 'An Ensemble Classification System for Twitter Sen-timent Analysis', Procedia Comput. Sci., vol. 132, pp. 937–946, Jan. 2018, doi: 10.1016/j.procs.2018.05.109.

[20] J. E. Dayhoff and J. M. DeLeo, 'Artificial neural networks', Cancer, vol. 91, no. 8, pp. 1615–1635, Apr. 2001, doi: 10.1002/1097-0142(20010415)91:8+<1615::AID-CNCR1175>3.0.CO;2-L.

[21] G. Schaefer, 'ACO classification of thermogram symmetry features for breast cancer diagnosis', Memetic Comput., vol. 6, no. 3, pp. 207–212, Sep. 2014, doi: 10.1007/s12293-014-0135-9.

[22] N. F. Abubacker, A. Azman, S. Doraisamy, and M. A. A. Murad, 'An inte-grated method of associative classification and neuro-fuzzy approach for effective mammographic classification', Neural Comput. Appl., vol. 28, no. 12, pp. 3967–3980, Dec. 2017, doi: 10.1007/s00521-016-2290-z.

[23] J. de N. Silva, A. O. de C. Filho, A. C. Silva, A. C. de Paiva, and M. Gattass, 'Automatic Detection of Masses in Mammograms Using Quality Threshold Clustering, Correlogram Function, and SVM', J. Digit. Imaging, vol. 28, no. 3, pp. 323–337, Jun. 2015, doi: 10.1007/s10278-014-9739-3.

[24] O. Manor and E. Segal, 'Predicting Disease Risk Using Bootstrap Ranking and Classification Algorithms', PLOS Comput. Biol., vol. 9, no. 8, p. e1003200, Aug. 2013, doi: 10.1371/journal.pcbi.1003200.

[25] C. Kooperberg, M. LeBlanc, and V. Obenchain, 'Risk prediction using ge-nome-wide association studies', Genet. Epidemiol., vol. 34, no. 7, pp. 643–652, doi: 10.1002/gepi.20509.

[26] M.-S. Cheung, M. L. Maguire, T. J. Stevens, and R. W. Broadhurst, 'DANGLE: A Bayesian inferential method for predicting protein backbone dihedral angles and secondary structure', J. Magn. Reson., vol. 202, no. 2, pp. 223–233, Feb. 2010, doi: 10.1016/j.jmr.2009.11.008.

Advances in Artificial Intelligence Research (AAIR)
ISSN 2757-7422
www.dergipark.com/aair/

Vol. 2 (No. 1), pp. 20-28, 2022
doi: 10.54569/aair.1017801
Published online: Feb, 16, 2022

Classification of Environmental Sounds With Deep Learning

Bekir Aksoy [1,*], Uygar Usta [1], Gürkan Karadağ [1], Ali Rıza Kaya [1], Melek Ömür [1]

[1] Isparta University of Applied Sciences, Department of Mechatronics Engineering

Abstract

Today, with the development of technology, environmental destruction is increasing day by day. For this reason, it is inevitable to take different measures to prevent the damage caused by environmental destruction. It is possible to prevent environmental damage by identifying the sounds that harm the environment and transferring them to the relevant units. In the study carried out, a data set of saw, rain, lightning, bark and broom sound data obtained from open access websites was created. Rain, barking and broom sounds in the data set were determined as the sounds that do not harm the environment, while saw and lightning were determined as the data set that harms the environment. The dataset was classified using VGG-13BN, ResNet-50 and DenseNet-121 deep learning architectures. When used, all three deep learning accuracy are due to over 95% study. Among these models, the VGG-13 BN model emerged as the most successful model with an accuracy rate of 99.72%.

Keywords: *Deep Learning; transfer learning; spectrogram; environmental sound detection*

1. Introduction

Environmental sustainability is essential for a high quality of life and a sustainable life. For this reason, it is of great importance that any situation that may destroy the environment can be prevented before the destruction occurs [1]. In order to prevent this destruction, it is very important to keep the damage to a minimum by classifying the sound obtained from the action taken or to inform the relevant institutions before the destruction occurs. For this purpose, it is possible to reduce the damage caused by environmental sounds by using different methods.

One of the methods used is the conversion of sound data obtained from the environment into spectrograms, which are a visual representation of the signal frequency spectrum, and classification using transfer learning [2, 3]. Spectrogram; is to calculate the frequency spectrum of an audio signal in each time slot and visually represent it on a time-frequency axis graphic, with the vertical axis frequency value and the horizontal axis time information [4]. The obtained signal is divided into certain parts and the spectrum of each part is processed to calculate. The sample image in Figure 1 is obtained by positioning these different spectra as vertical lines next to each other to create a two-dimensional image.

With the spectrogram method, it is aimed to reduce the frequency structure of audio parts to a very simple structure. To summarize; spectrogram is a visual representation of sound [5,6].

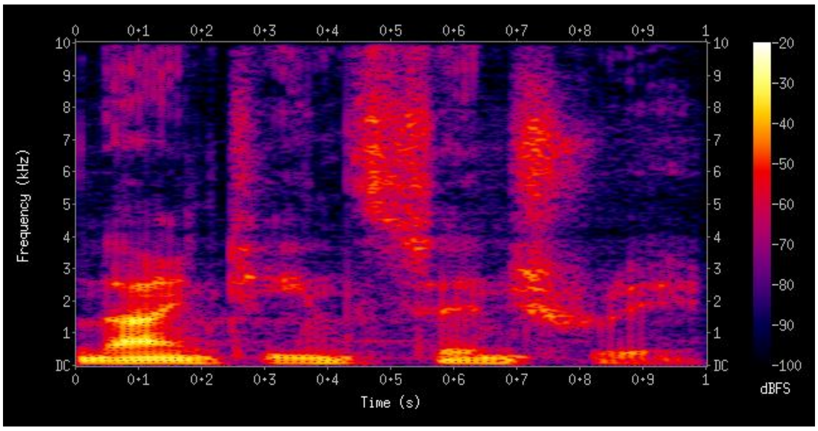


Figure 1. *Spectrogram showing frequency (Hz) and time (time) range*

One of the important usage areas of spectrogram transformation is artificial intelligence applications. When the academic studies on spectrogram transformation based on artificial intelligence are examined, the algorithm extracts the features in the image and the problem turns into a picture classification problem [7]. Thus,

*Corresponding author
E-mail address: bekiraksoy@isparta.edu.tr

Received: 02/Nov/2021; Received in revised form: 01/Feb/2022; Accepted: 01/Feb/2022.

successful results can be obtained without using a complex method. ResNet-50 algorithm is used in transfer learning [8]. As a result of the classification, an average of 90% success was achieved. Experimental results that have been tried on the prototype created data set show that the system can be used successfully in the task of classifying environmental sounds and preventing destruction. It can also be used in solving different problems in daily life by changing some components such as the data set in this proposed system. In addition, this system can perform at an equivalent level when compared to the advanced methods used in the literature.

Sainath Adapa (2019) proposed a structure for environmental noise classification with a low number of data (less than 100 labeled data per class). He stated that in this structure, using transfer learning models together with the data augmentation method, higher performance is achieved compared to alternative approaches. He used this structure in Urban Voice recognition [9].

Muhammad Huzaifah (2017) proposed the visualization of an audio signal through various time-frequency representations such as Spectrograms, as these representations are a rich representation of the temporal and spectral structure of the original signal. To obtain such a representation, the waveform transforms, the constant Q transform, and the Mel measurements were compared and used two different datasets in CNN networks to evaluate their effects on classification performances [10].

Zhichao Zhang, Shugong Xu, Shan Cao, and Shunqing Zhang (2018) used convolutional and pooling layers to extract high-level feature representations from network architecture, spectrogram-like features. They observed the effects of network architectures on performance and feature distributions in different datasets [11].

Justin Salamon and Juan Pablo Bello (2016) argue that the success of deep convolutional neural networks in learning the distinctive features of spectral-temporal patterns makes these networks suitable for environmental sound classification. However, it has been argued that the relative scarcity of labeled data precludes exploitation of this family of high-capacity models. These studies have two contributions to the literature: first, a deep convolutional network architecture is proposed for environmental sound classification. Second, it is proposed to use voice data augmentation to overcome the problem of data scarcity [12].

Juncheng Li, Wei Dai, Florian Metze*, Shuhui Qu, and Samarjit Das (2017) conducted experiments on six different feature sets in their studies. These sets used Mel-frequency cepstral coefficients, binaural mel-frequency cepstral coefficients, log mel-spectrum and two different temporal pooling features. Deep neural network models using large data sets surpass traditional models in performance and stated that they have the highest performance among all the methods studied [13].

A total of 713 voice data obtained from open access websites were used in the study. It is aimed to reduce the damage by classifying the environmental sounds with the use of deep learning methods in the created data set. It is aimed to reduce the damage by classifying the environmental sounds with the use of three different deep learning methods, the data set Resnet-50, DenseNet-121 and VGG-13 BN. Among the three different deep learning architectures used, VGG-13 BN was determined as the deep learning architecture that classifies sounds with 99.72% accuracy.

2. Materials and Method

2.1. Materials

In the study, a data set created from environmental sounds found on open-source websites was used. There are 713 pieces of data in the data set. The dataset consists of 5 different classes: barking, chainsaw, thunder, rain and vacuum cleaner. The dataset was trained with transfer learning using VGG-13BN, ResNet-50 and DenseNet-121 architectures. The results obtained from the architectures were analyzed over the performance evaluation criteria of sharpness, f1 score, sensitivity and accuracy [14, 15]. It was tested using data not available in the post-analysis data set. The data set used in the study, deep learning algorithms and performance evaluation criteria are given in detail below.

2.1.1. Data Set

Each data that makes up the data set has been downloaded from various internet sites in the form of audio files with the extension "wav". Data with different extensions were taken as video clips from open source platforms on the internet and converted into audio data with wav extension. The data set consists of 5 classes: barking, chainsaw, thunder, rain and vacuum cleaner. Among these classes, the sounds of thunder, chainsaw and rain were chosen as the sounds that could cause environmental destruction. Dog barking and vacuum cleaner are included as distinctive sounds. In the dataset, there are approximately 140 voice data belonging to each class. Audio data is converted into spectrograms, which are a visual representation of the frequency spectrum of the signal. With this transformation, audio data is transformed into images and classified. Of the 140 data per class, 80% was used in training and the remaining 20% in testing. An example of a spectrogram is shown in Figure 2.

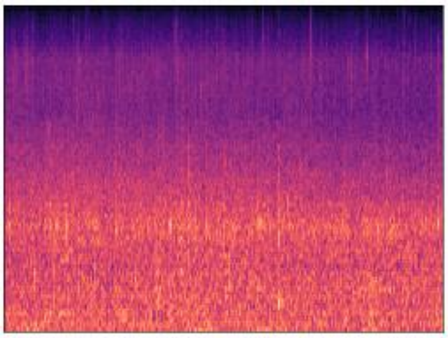


Figure 2. *Spectrogram image formed by preprocessing a sound data*

2.1.2 Deep Learning Architectures

2.1.2.1. VGG 13 BN

VGG-based deep learning methods are frequently used in many areas. One of these architectures, VGG 13 BN architecture, was used in the study. The VGG-13 BN architecture consists of 13 layers (10 convolutional layers + 3 fully connected layers). In the VGG 13 BN architecture, stack normalization layers are used after the convolutional layers [16]. 224x224 images are used as input. In convolutional layers, 3x3 kernels are used. In the pooling layers, the shift value is 2 and the kernel size is 2x2 [17].

2.1.2.2. DenseNet-121

One of the artificial intelligence methods used for images is the DenseNet-121 model. In the DenseNet-121 model, traditional convolutional networks with the number of layers L have L connections, while the DenseNet architecture has as many connections as L(L+1)/2. For each layer, feature maps of previous layers are used as input, and its own feature maps are used as input for all subsequent layers [18, 19]. One of the important advantages of DenseNet architectures is that it reduces the gradient disappearance problem [20, 21].

Thus, it significantly reduces the number of parameters by reusing the features while enhancing the feature dispersion. The DenseNet architecture is shown in Figure 3 [22]. DenseNet-121 architecture consists of 121 layers [23].

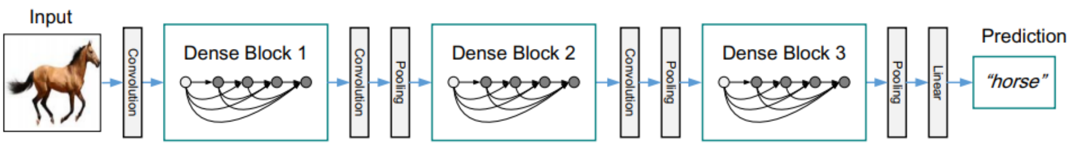


Figure 3. *DenseNet Architecture [22]*

2.1.2.3. ResNet-50

The third deep learning architecture used in the study is the Resnet-50 architecture. ResNet architecture has a high number of layers [24]. It is a deep learning architecture created to solve the problem of performance degradation in convolutional neural network architectures due to the large number of layers [25]. However, networks with a large number of layers achieve success as the depth increases, but after a while, they tend to decrease due to the disappearance of the gradients. To avoid this downward trend, ResNet architectures use hopping connections. By adding jump links, gradients can be easily moved from layer to layer. Thus, from the first layer, even the lowest layers can access the activations in the upper layers, so very deep networks can be trained with ResNet architectures [26].

2.1.3 Performance Evaluation Criteria

Since the classification process was carried out using deep learning methods in the study, sharpness, accuracy, F1 score and sensitivity methods were used to evaluate the performance of the models. The results obtained according to the precision, accuracy, F1 score and sensitivity performance evaluation criteria of the models trained with deep learning architectures are evaluated on the complexity matrix and correct and incorrect predictions are obtained for each class. In Table 1, the complexity matrix structure is shown in tabular form [27].

Table 1. *Structure of the Complexity Matrix*

		ESTIMATED VALUE	
		POSITIVE	**NEGATIVE**
REAL VALUE	**POSITIVE**	TRUE POSITIVE (TP)	FALSE POSİTİVE (FP)
	NEGATIVE	FALSE NEGATİVE (FN)	TRUE NEGATİVE (TN)

2.1.3.1 Precision

Precision answers the question of how accurate the positive predictions are in its models. Equalized as defined at Eq. (1).

$$\text{Precision} = \frac{TP}{TP+FP} \tag{1}$$

2.1.3.2 Sensivity

Sensitivity answers the question of how accurately true positives are detected in classification models. It is expressed mathematically in Eq. (2).

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{2}$$

2.1.3.3 F1 Score

The F1 score shows us the harmonic mean of the precision and sensitivity values. It is expressed mathematically in Eq. (3).

$$\text{F1} = \frac{2* Precision *Sensitivity}{Precision+Sensitivity} \tag{3}$$

2.1.3.4 Accuracy

Accuracy is used to measure the success of the model, but it is not sufficient by itself. It is expressed mathematically in Eq. (4).

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{4}$$

Mathematical expressions of the mean of accuracy, sensitivity [28-30], f1 score and precision [29-30] measurements calculated for each class when performing performance evaluations in multi-class problems (more than 2 classes) are given in Eqs. (5)-(8);

$$\text{Average Precision} = \frac{\sum_{i=1}^{N} \frac{TP_i}{TP_i+FP_i}}{N} \tag{5}$$

$$\text{Average Sensitivity} = \frac{\sum_{i=1}^{N} \frac{TP_i}{TP_i+FN_i}}{N} \tag{6}$$

$$\text{Average F1 Score} = \frac{\sum_{i=1}^{N} \frac{2* Precision_i * Sensitivity_i}{Precision_i+Sensitivity_i}}{N} \tag{7}$$

$$\text{Average Accuracy} = \frac{\sum_{i=1}^{N} \frac{TP_i+TN_i}{TP_i+FP_i+TN_iFN_i}}{N} \tag{8}$$

2.2. Method

Work flow diagram of the classification of environmental sounds with deep learning is given in Figure 4. In the first stage, a data set was created with the audio data found on open source websites. The data set consists of 5 classes. These classes are bark, thunder, rain, vacuum cleaner and chainsaw sound. There are 140 pieces of data for each class. As a preprocessing step, the audio data were converted into spectrograms and converted into images. Images were trained with DenseNet-121, ResNet-50 and VGG-13 BN deep learning algorithms. 80% of the data in the data set was used for training and 20% for testing. A learning rate of 0.003 was used for each algorithm. Then, the test results of the algorithms were obtained by making predictions with the data that is not in the data set.

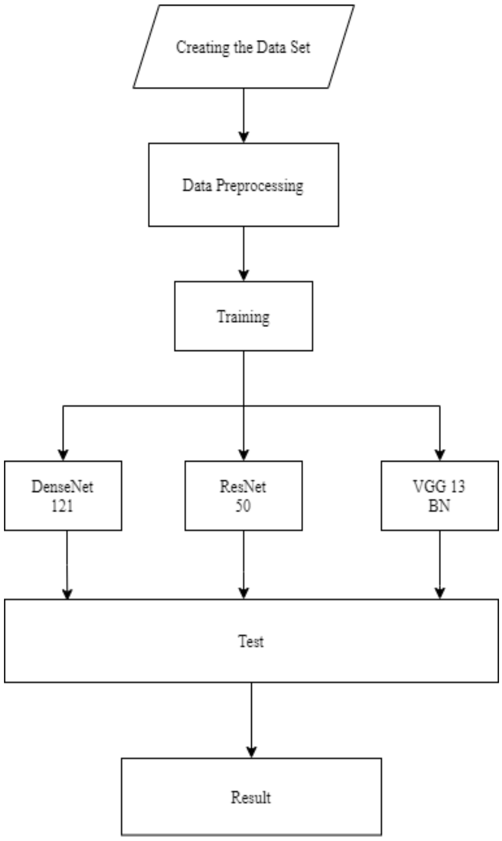
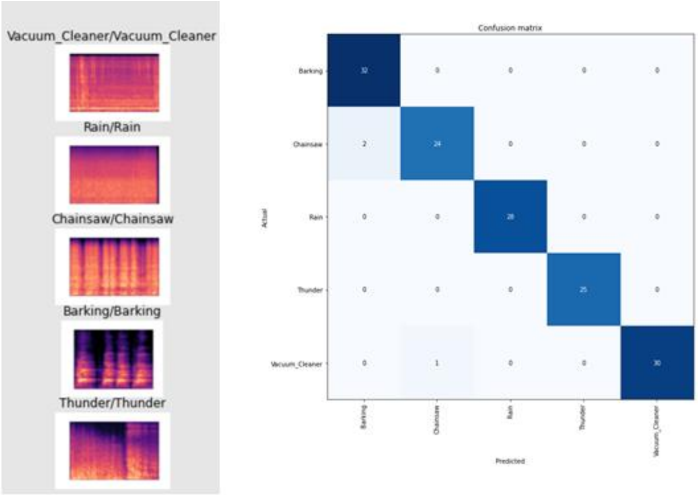


Figure 4. *Work flow diagram*

3. Research Findings

In the study, three different models of sound data were trained using ResNet-50, DenseNet-121 and VGG-13 BN deep learning models. After the training, the model was evaluated according to the performance evaluation criteria by examining the complexity matrices. After the evaluation, the models were tested using an image that was not in the data set for each class, and the following results were obtained. In Figure 5, the test and complexity matrix results of the ResNet-50 model are given.



(a) (b)

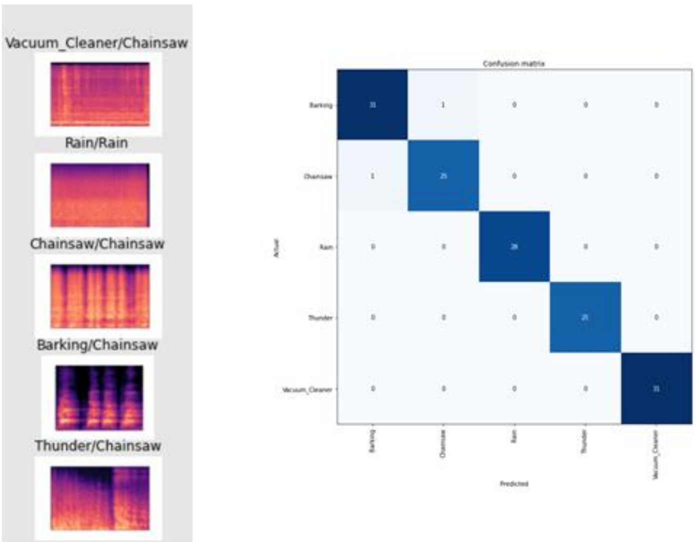
Figure 5. *ResNet-50 (a) test result, (b) complexity matrix*

When the complexity matrix is examined, 142 test data according to the ResNet-50 model are examined; He classified 32 of the 34 test data belonging to the Barking class as correct and 2 as incorrect (Chainsaw). It classified 24 of 25 test data belonging to Chainsaw class as correct and 1 as incorrect (Vacuum_Cleaner). It correctly classified all 28 test data belonging to the Rain class. It correctly classified all 25 test data belonging to the Thunder class. It correctly classified all 30 test data belonging to the Vacuum_Cleaner class. The performance evaluation criteria of the ResNet-50 model are shown in Table 2.

Table 2. *Performance Evaluation Criteria*

Precision	Sensitivity	F1 Score	Accuracy	Test
0.98	0.976	0.975	0.9912	5/5

When Table 2 is examined, it is seen that the ResNet-50 architecture has been successfully classified over 97% according to all performance evaluation criteria. The test result (a) and complexity matrix (b) of the DenseNet-121 model are given in Figure 6.



(a) (b)

Figure 6. *DenseNet-121 (a) test result, (b) complexity matrix*

When the complexity matrix is examined, 142 test data according to the DenseNet-121 model are examined; He classified 31 of the 32 test data belonging to the Barking class as correct and 1 as incorrect (Chainsaw). It classified 25 of the 26 test data belonging to the Chainsaw class as correct and 1 as incorrect (Barking). It correctly classified all 28 test data belonging to the Rain class. It correctly classified all 25 test data belonging to the Thunder class.

It correctly classified all 31 test data belonging to the Vacuum_Cleaner class. The performance evaluation criteria of the DenseNet-121 model are shown in Table 3.

Table 3. Performance *Evaluation* Criteria.

Precision	Sensitivity	F1 Score	Accuracy	Test
0.9858	0.9858	0.9858	0.99438	2/5

The test result (a) and complexity matrix (b) of the VGG-13 BN model are given in Figure 7.

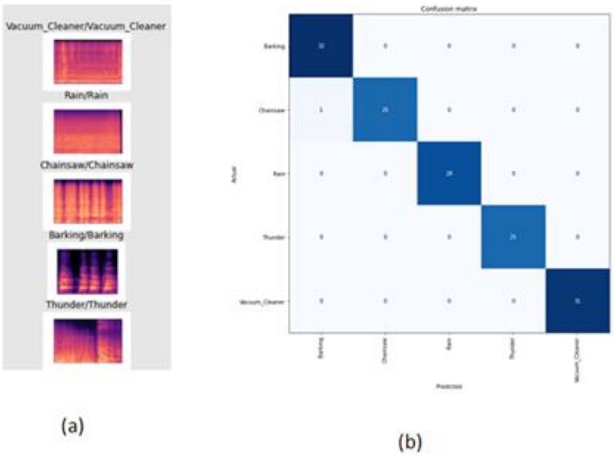


Figure 7. *VGG-13 BN (a) test result, (b) complexity matrix*

When the complexity matrix is examined, 142 test data according to the VGG-13 BN model are examined; He classified 32 of the 33 test data belonging to the Barking class as correct and 1 as incorrect (Chainsaw). It correctly classified all 25 test data belonging to the Chainsaw class. It correctly classified all 28 test data belonging to the Rain class.

It correctly classified all 25 test data belonging to the Thunder class. It correctly classified all 31 test data belonging to the Vacuum_Cleaner class. The performance evaluation criteria of the VGG -13 BN model are shown in Table 4.

Table 4. *Performance Evaluation Criteria.*

Precision	Sensitivity	F1 Score	Accuracy	Test
0.9938	0.9922	0.9928	0.9972	5/5

In Table 5, the results of the performance evaluation criteria of three different deep learning architectures used in the study are given.

Table 5. *ResNet-50, DenseNet-121 and VGG-13 BN Performance Evaluation Criteria*

Model	Precision	Sensitivity	F1 Score	Accuracy	Test
ResNet-50	0.98	0.976	0.975	0.9912	5/5
DenseNet-121	0.9858	0.9858	0.9858	0.99438	2/5
VGG-13 BN	**0.9938**	**0.9922**	**0.9928**	**0.9972**	**5/5**

When Table 5 is examined, it is seen that all three architectures have an accuracy rate of over 97%. Among these three architectures, according to the VGG 13 BN accuracy performance evaluation criterion, approximately 1.78% more successful performance was obtained compared to the ResNet-50 architecture and approximately 0.7% more successful than DenseNet-121.

4. Result

Today, the damages caused by environmental sounds have become more important with the advancement of technology. In the study carried out, five different environmental sounds were classified as Barking, Chainsaw, Rain, Thunder, VacuumCleaner with ResNet-50, DenseNet-121 and VGG-13 BN architectures. The results obtained from the architectures were evaluated according to four different performance evaluation criteria, and deep learning models were tested for each class by using an image that was not included in the data set. According to the performance evaluation criteria, the most successful model was found to be VGG-13 BN with 99.38% acuity, 99.22% sensitivity, 99.72% accuracy and 99.28% F1 score. In addition, the images that are not in the data set were tested on the models and it was determined that the deep learning models predicted all the images correctly. The ResNet-50 model performs very close to the VGG-13 BN model when the performance evaluation criteria and test results are examined. Although the performance evaluation criteria scores of the ResNet-50 model are lower than DenseNet-121, it has been determined that it performs better when looking at the test results. Thus, it was determined that the ResNet-50 model had a better test result than the DenseNet-121 model.

According to the results obtained from deep learning architectures in the study, it was seen that the best models that can be used in environmental sound detection are VGG 13-BN and ResNet-50. It is thought that performance can be increased with different deep learning architectures by using transfer learning on the data set used in further studies. In future academic studies, it is planned to increase the number of environmental sounds and to carry out different studies by using different deep learning architectures.

Acknowledgement

We would like to thank everyone who made the data sets consisting of environmental sounds used in the study available as open source on different websites.

References

[1] Önder S, Gülgün B. "Gürültü Kirliliği Ve Alınması Gereken Önlemler: Bitkisel Gürültü Perdeleri". *Ziraat Mühendisliği*, 35, 54-64, 2010.

[2] Felipe G Z, Maldonado Y, da Costa G, Helal L G. "Acoustic scene classification using spectrograms". *In 2017 36th International Conference of the Chilean Computer Science Society (SCCC)*, 1-7, 2017.

[3] Olah C. (2020). Understanding lstm networks, August 2015. *URL https://colah. github. io/posts/2015-08-Understanding-LSTMs*. Accessed on, 10.

[4] Nwe T L, Dat T H, Ma B. "Convolutional neural network with multi-task learning scheme for acoustic scene classification". *In 2017 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, 1347-1350, 2017.

[5] Kodaloğlu G. Segmentation of snore sounds and detection of sleep apnea with statistical change detection algorithms. *MSc Thesis*, Ankara University, Ankara, Turkey, 2019.

[6] Başbuğ A M. Sound event recognition and acoustic scenes retrieval. *MSc Thesis*, Başkent University, Ankara, Turkey, 2019.

[7] Toraman S, Arslan Tuncer S, Balgetir F. "Is it possible to detect cerebral dominance via EEG signals by using deep learning?" *Medical Hypotheses*, Elazığ: Fırat University, 131, 2019.

[8] Talo M. "Meme Kanseri Histopatolojik Görüntülerinin Konvolüsyonal Sinir Ağları ile Sınıflandırılması". *Fırat University Journal of Engineering Science*, 31(2), 391-398, 2019.

[9] Adapa S. "Urban sound tagging using convolutional neural networks". *arXiv preprint arXiv:1909.12699v1*, 2019.

[10] Huzaifah M. "Comparison of time-frequency representations for environmental sound classification using convolutional neural networks". *arXiv preprint arXiv:1706.07156*, 2017.

[11] Zhang Z, Xu S, Cao S, Zhang S. "Deep convolutional neural network with mixup for environmental sound classification". *In Chinese conference on pattern recognition and computer vision (prcv)*, 356-367, 2018.

[12] Salamon J, Bello J P. "Deep convolutional neural networks and data augmentation for environmental sound classification". *IEEE Signal processing letters*, 24(3), 279-283, 2017.

[13] Li J, Dai W, Metze F, Qu S, Das S. "A comparison of deep learning methods for environmental sound detection". *In 2017 IEEE International conference on acoustics, speech and signal processing (ICASSP)*, 126-130, 2017.

[14] Özkaya U, Seyfi L. "Yere Nüfuz Eden Radar B Tarama Görüntülerinin Az Parametreye Sahip Konvolüsyonel Sinir Ağı İle Değerlendirilmesi". *Geomatik*, 6(2), 84-92, 2021.

[15] Bozkurt F, Yağanoğlu M. “Derin Evrişimli Sinir Ağları Kullanarak Akciğer X-Ray Görüntülerinden COVID-19 Tespiti”. *Veri Bilimi*, 4(2), 1-8, 2021.

[16] Turhan C G, Bilge H Ş. “Çekişmeli üretici ağ ile ölçeklenebilir görüntü oluşturma ve süper çözünürlük”. *Journal of the Faculty of Engineering and Architecture of Gazi University*, 35(2), 953-966, 2020.

[17] Akılotu B N, Kadiroğlu Z, Şengür A, Kayaoğlu M. “Evrişimsel Sinir Ağları ve Transfer Öğrenme Yöntemi Kullanılarak Sıtma Tespiti”. *International Engineering and Science Symposium, Siirt,* 2019.

[18] Bozkurt F. “Derin Öğrenme Tekniklerini Kullanarak Akciğer X-Ray Görüntülerinden COVID-19 Tespiti”. *Avrupa Bilim ve Teknoloji Dergisi*, 24, 149-156, 2021.

[19] Kumar R. “Adding binary search connections to improve densenet performance”. In *5th International Conference on Next Generation Computing Technologies (NGCT-2019)*, 2020.

[20] Korfiatis P, Kline T L, Lachance D H, Parney I F, Buckner J C, Erickson B J. “Residual deep convolutional neural network predicts MGMT methylation status”. *Journal of digital imaging*, 30(5), 622-628, 2017.

[21] Fu Y, Aldrich C. “Flotation froth image recognition with convolutional neural networks’’. *Minerals Engineering*, 132, 183-190, 2019.

[22] Huang G, Liu Z, van der Maaten L, Weinberger K Q. “Densely connected convolutional networks”. *In Proceedings of the IEEE conference on computer vision and pattern recognition*, 4700-4708, 2017.

[23] Li X, Shen X, Zhou Y, Wang X, Li T Q. “Classification of breast cancer histopathological images using interleaved DenseNet with SENet (IDSNet)’’, *PloS one*, Hangzhou: China Jiliang University, 15(5), e0232127, 2020.

[24] Duman E, Akın F. “Yüz Tanima Sürecinde Farkli Cnn Modellerinin Performans Karşilaştirmasi’’. *Uluslararası Mardin Artuklu Multidisipliner Çalışmalar Kongresi*, 35-42, 2019.

[25] Narin A. “Meme Kanserinin Evrişimsel Sinir Ağı Modelleriyle Tespitinde Farklı Görüntü Büyütme Oranlarının Etkisi’’. *Karaelmas Fen ve Mühendislik Dergisi*, 10(2), 186-194, 2020.

[26] Tan Z. Vehicle classification with deep learning. *MSc Thesis*, Fırat University, Elazığ, Turkey, 2019.

[27] Deng X, Liu Q, Deng Y, Mahadevan S. “An improved method to construct basic probability assignment based on the confusion matrix for classification problem”. *Information Sciences*, 340, 250-261, 2016.

[28] Orman A, Köse U, Yiğit T. “Açıklanabilir Evrişimsel Sinir Ağları ile Beyin Tümörü Tespiti”. *El-Cezeri*, 8(3), 1323-1337, 2021.

[29] Sokolova M, Lapalme G. “A systematic analysis of performance measures for classification tasks”. *Information processing & management*, 45(4), 427-437, 2009.

[30] Ballabio D, Grisoni F, Todeschini R. “Multivariate comparison of classification performance measures”. *Chemometrics and Intelligent Laboratory Systems*, 174, 33-44, 2018.

Advances in Artificial Intelligence Research (AAIR)
ISSN 2757-7422
www.dergipark.com/aair/

Vol. 2 (No. 1), pp. 29-37, 2022
doi: 10.54569/aair.1016850
Published online: Feb 16, 2022

An Artificial Neural Network Model Based on Experimental Measurements for Estimating the Grounding Resistance

Ahmet Kayabasi [1], Berat Yildiz [1,2,*], Selami Balci [3]

[1] Karamanoglu Mehmetbey University, Department of Electrical and Electronics Engineering, Karaman, Turkey;
[2] Konya Technical University, Department of Electrical and Electronics Engineering, Konya, Turkey;
[3] Karamanoglu Mehmetbey University, Department of Electrical and Electronics Engineering, Karaman, Turkey;

Abstract

In grounding systems established in rocky and sandy lands where contact resistance with metal electrodes is high, contact resistance is generally the most critical parameter that changes the total grounding resistance value. Therefore, the nonlinear variation of the earth contact resistance according to the soil type cannot be taken into account in determining the grounding resistance with the traditional mathematical formulas given theoretically. This reduces the accuracy of grounding resistance determination. In this study, experimental measurements were made according to soil types and a data set was created. Then, to estimate the total grounding resistance of complex grounding systems, a classification was made using the multi-layer sensor (MLP) type ANN algorithm and the successful results were reported. Thus, according to the data set prepared based on experimental measurements, the proposed general classification algorithm approach can be applied to any grounding system. It presents a different technique from the previous literature as a pre-feasibility study for estimating the grounding resistance, especially before the grounding system installation, which is an early stage of the design process.

Keywords: *Grounding systems, grounding resistance measurement, parameter classification, soil type*.

1. Introduction

Today, electrical energy, as an indispensable type of energy, is vital in daily life, and possibly electrical and insulation faults that may occur during the use of electrical energy can pose a danger to the life of living things. Therefore, various protection measures such as grounding, insulation, and the use of low voltage must be taken to protect the life of living things and the system in electrical installations [1]. Grounding systems, an extremely safe protection measure, are the critical components of the protection system against lightning and fault currents of facilities, substations, transmission, and distribution lines in general electrical installations. These systems are primarily designed for ground fault conditions at mains frequency values and transfer high-value leakage currents (30 mA and above) to the ground. Thus, grounding systems that are correctly installed and follow the reliable requirements of the relevant international standards can safely distribute high-value fault currents to the ground; in this way, it protects life and property from harm and damage. In infield application, all elements of the grounding system are interconnected. They can perform their duty to safely transfer both power frequency faults and lightning impulse currents to the ground. On the other hand, for a grounding system to function effectively, the ground resistance value must be kept at low levels during the use of the electrical facility.

The international standards [2] specify the effects of meteorological issues such as humidity, temperature, and soil compaction on soil resistivity and recommend periodic measurement of soil resistance values to keep them under control. However, most electrical installations in rocky areas require high costs in installing grounding systems, from lack of suitable location or preventing installation. Besides, the ground resistivity of the top layer is subject to seasonal changes due to weather conditions such as precipitation, ice, and air temperature, which mainly affect ground moisture. At the same time, the percentage of dissolved salt and soil consistency plays an essential role. The effect of ground resistivity *(ρ)* on the value of ground transition resistance *(R_g)* is very high. It varies depending on humidity, temperature, salt content, soil type, which differs significantly seasonally throughout the year. In addition, ground resistance reaches very high values in the summer months when the moisture in the ground layers decreases [3]. In recent years, the use of ground reformative compounds to soften the ground, resulting in reduced ground resistance, has been increasingly popular in engineering. Those are generally used in high resistive ground types and must fully comply [4]. Therefore, numerous research studies have been conducted in the past literature examining and observing the performance of these materials and their effects on the ground resistance of various grounding systems [5].

In this study, unlike other studies, an experimental data set consisting of 200 data was created to determine the nonlinear changes of the grounding resistance with complex dry-stony and wet-stone free soil structures.

*Corresponding author
E-mail address:yildizberat2086@gmail.com

Received: 31/Oct/2021; Received in revised form: 06/Feb/2022; Accepted: 10/Feb/2022.

This data set was trained using multilayer perceptron (MLP) type ANN, and successful results were obtained in estimating the classification of grounding resistance of complex grounding systems.

The remaining content of the article is organized as follows. A general literature review about artificial intelligence techniques applied in grounding systems is explained in the second part. The third part gives the applied methods and the materials used. Obtained results are interpreted in the fourth chapter. In the fifth, that is, the conclusion part, the results of the article, and future studies are mentioned.

2. Related Work

The value of the ground resistance varies greatly depending on the grounding system and the characteristics of the ground in which the system is buried. Considering that ground resistivity fluctuates depending on the season during the year, there is no definite value for ground resistance. In [6], it was aimed to develop a methodological approach to predict soil resistivity using artificial intelligence techniques. For this, linear and nonlinear relationships between various parameters are defined using Artificial Neural Networks (ANNs). In a study using ANN [3], based on temperature and precipitation measurements for a year, tests were conducted with various algorithms for their ability to predict soil resistance, and an optimization procedure was proposed to select the parameters of each training algorithm. Thus, the effectiveness of the ANN is proven by the high correlation index between the estimated and measured values of the ground resistance. In another study on meteorological data [7], a suitable genetic programming methodology was used to model and predict the measurement results of grounding resistance values in the field. The experimental data carried out in this context were field measurements in Greece for approximately four years. An intelligent approach based on Gene Expression Programming (GEP) was proposed, and additionally, five linear regression models were applied to a specially selected data set. The obtained results showed that evolutionary techniques such as those based on Genetic Programming (GP) are promising for predicting ground resistance.

It is of great importance for electrical engineers to provide as low as possible values for grounding resistance during the design phase and the life cycle of the grounding system. In case of high ground resistivity values or insufficient space for installing grounding systems, a commonly used technique to reduce the grounding resistance value is the use of ground-reinforcing custom-made compounds. For this purpose, in a study conducted in the past literature [8], a particular methodology developed with ANN to determine the grounding resistance of naturally buried grounding electrodes using soil enrichment compounds under various meteorological conditions is proposed.

In the studies conducted to determine the soil resistance value in the past literature [5], entropy knowledge-based inductive learning techniques are recommended for testing the performance of grounding systems according to ground resistance and precipitation data estimating possible changes in ground resistance values. For this purpose, ground resistivity and precipitation density measurements were made at various ground depths in a particular university campus area over four years. Ground resistance values of several grounding rods coated with ground strengthening compounds were obtained as a function of time. Decision trees were created to approximate the ground resistance to the discrete-valued target function to model these obtained data. They were represented by production rules to make the model understandable. The v-fold cross-validation approach determined error rates and performance of the model on invisible states. Thus, inductive machine learning primarily aims to achieve high accuracy, not as a classifier and is used more as a knowledge discovery tool that can be controlled with statistical techniques.

The proposed model in [9] consists of a Wavelet Neural Network trained and validated by field measurements performed for the last three years. Soil reinforcement compounds and several ground rods placed in natural soil were tested to obtain a large dataset for training the network covering various soil conditions. Thus, this study introduces wavelet analysis in ground resistance estimation and tries to benefit from the benefits of artificial intelligence.

An estimator for the grounding resistance value is proposed to study the grounding electrodes' total length and geometric properties [10]. This proposed approach is valid for a ground-embedded electrode system that can be considered almost homogeneous with various assumptions. It is generally confirmed that more accurate resistance estimation can be made as the size of the electrodes gets larger.

The study [11] aimed to derive simple formulas for predicting the grounding resistance value of wind farms installed in terrains that can be designed with a two-layer grounding system. Different combinations of grounding resistance values for the top and bottom layer of two-layer grounding systems and the depth of the top layer are carefully determined to cover a wide variety of irregularities in the earth. Then, the grounding resistance values are selected from the simulation studies run for a combination between the investigated bilayer models and the predefined ground electrode geometry.

It is known that the grounding systems are a crucial component for the safe operation of the electrical grid, transmission, distribution, and electrical power systems in general. However, the researchers have limited knowledge of the soil resistance variation of the region at the design stage. In addition, the grounding resistance periodical measurement is often hampered by residential infra-structure. Therefore, a model has been developed in [12] that correctly describes the dynamics of grounding resistance variation based on the engineers' need for the flexibility and reliability of determining the behavior of the grounding systems. Thus, the developed model has trained in-field soil resistivity and precipitation height measured over four years from a nonlinear and non-parametric wavelet neural network (WNN). Next, the proposed framework was tested with different ground reinforcing compounds in five (5) other grounding systems. The obtained research results show that WNN can create an accurate model for soil resistance estimation and can be a valuable tool for electrical engineers.

A precondition for the correct and reliable grounding system design is full knowledge of the earth structure at the installation region. Engineers can show the ground profile, the most critical parameter for designing a grounding system and determining the maximum allowable step and touch voltage limits thanks to ground resistivity measurements. In [13], it highlights the importance and necessity for engineers to select appropriate ground resistivity measurement axes in the terrain of interest and correct measurement depths and combinations of axes for the final determination of the earth profile. In this context, it is also proven that appropriate and pre-planned measurement of ground resistance, especially in the non-isotropic ground, is of great importance for the precise design of a safe grounding system.

The primary purpose of the work in [14] is to investigate the prediction of soil resistance change during a year using ANN. An ANN modeling was carried out with the different algorithms using earth (soil) resistivity and experimental precipitation data to select the optimum training algorithm and related parameters and determine the behavior of the soil resistivity of a single rod. Thus, the high value of the correlation index of the modeled and experimental values indicates the high efficiency of the ANN. The proposed methodology based on ANN has been a valuable tool for estimating grounding resistance throughout the year despite the challenges in measuring its value.

In this study, experimental measurements were made to determine the nonlinear variation of the grounding resistance value according to the soil type. Then, a classification has been made to estimate the grounding resistance values of complex grounding systems, and the results have been reported.

3. Method and Material

In rocky and sandy lands where the contact resistance is high in grounding systems established using copper electrodes in general, contact resistance is the most critical parameter that generally changes the total grounding resistance value. In this context, since the ground contact resistance value cannot be considered exact, the degree of accuracy in determining the grounding resistance with the traditional mathematical formulas given theoretically is not very high. In this section, firstly, information about the measurement of grounding resistance value as an experimental study used to create the data set is given. Then, the artificial intelligence technique approach used to classify the obtained data set is explained.

3.1. Ground resistivity measurements

Two-point and four-point methods are frequently used in electrical installations to measure the ground resistance value experimentally. The four-point method (Wenner) is the most accurate in practice [12], [16]. Therefore, the Wenner method was applied in the measurements in the experimental part of this study. As shown in **Figure 1**, four 50 cm long electrodes were buried in the ground at equal distances from each other at depth b in the measurements made.

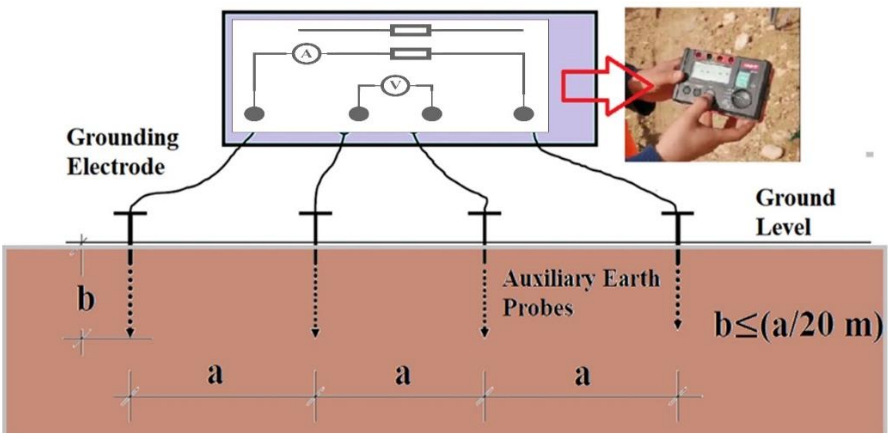


Figure 1. *Principle diagram of measurement with the Wenner method [15]*

Thus, a test current (I) flows into two electrodes, and the potential (V) between two medium electrodes is measured. The V/I ratio gives the visible resistance R(Ω). The visual ground resistance value can be approximately provided by Eq. (1) [2] with mathematical expression.

$$\rho = \frac{4\pi a R}{1+2a/\sqrt{a^2+4b^2}-a/\sqrt{a^2+b^2}} \quad (1)$$

Here, the distance a must be at least 20 m, with b≤(a/20). R gives the measured resistance value, and ρ offers the specific earth resistance value in Ωm. This measurement should be made with the four-probe method, and unique devices used in experimental studies have been developed to apply the Wenner Method in practice. The measurement principle is that a voltage of up to 150 Hz is applied between the outer electrodes. The voltage between the inner probes due to the current flowing is measured. The specific earth resistance is calculated using the resistance value calculated from the measured voltage and current value with the intermediate distance value. In advanced earth resistance measuring instruments, the specific resistance is directly read from the screen by entering the distance between the electrodes. The voltage frequency to be applied should be variable to eliminate the effect of other currents in the ground at the measurement site.

3.2 ANN model

ANN is a sub-branch of artificial intelligence that collects examples and generalizes [17-18]. It can classify by comparing the linear or nonlinear relations obtained from the samples with the data it has never encountered before [19]. Thanks to its learning and generalization functions, ANN is involved in many scientific studies and can offer solutions to complex problems [20-25]. The ANN structure consists of three essential layers: input, output, and hidden layers. The information processing function is performed in these layers, where each neuron is connected to other neurons by weight values **(Figure 2).**

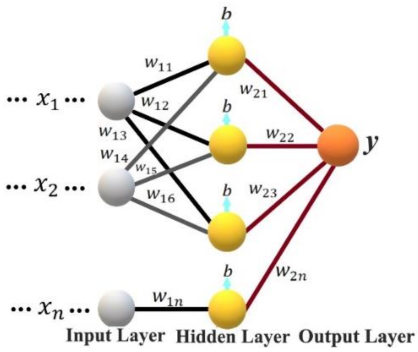


Figure 2. *The basic ANN structure*

The different values data set is transmitted directly to the input layer during the training and testing phases. Then, mathematical operations such as addition, multiplication, and activation functions are applied in the hidden layers. Finally, this data is transmitted to the output layer. The difference between the input and output layers is minimized by associating them with the mathematical expressions applied in the hidden layers. As this difference decreases, the learning function is performed. More than one hidden layer may be used depending on the complexity between the input and output data. The outputs of the neurons in the layers are formed by the expression given in Eq. (2).

$$y = f\left(\sum_{i=1}^{n} x_i w_{ij} + b\right) \quad (2)$$

Here, the input parameters presented to the network are x_i, the weight values w_i produced by the network according to the output value, the bias value *b*, the activation function *f(.),* and the output value yi.

Perceptrons are unsuccessful in solving problems that cannot be classified linearly. MLP is a multi-layered network that works particularly well in nonlinear classification and generalization situations. Learning in this type of network is based on the Delta Learning Rule. The main purpose of this rule is to minimize the error between the expected output of the network and the output it produces. Since it does this by spreading the error to the network, this network is called the error propagation network. In this study, the previously collected grounding resistance data which are non-linear were trained and classified using multilayer perceptron (MLP) type ANN. There are two classes in the dataset: Dry and Stony ground resistance labeled with 1 and Wet and Stone Free ground resistance labeled with 2. Each class contains 100 measured data. The training was carried out using the ANN structure given in **Figure 3**. 'logsig' (Logarithmic Sigmoid), 'logsig', and 'purelin' activation functions are used in the hidden layers of this network structure, which imparts nonlinear behavior to layer inputs, respectively. In addition, the parameters of the network architecture such as Adapt Function and Training Function which are given in **Table 1,** were chosen to overcome the Vanishing and Exploding gradient problems and to prevent the memorization of the network.

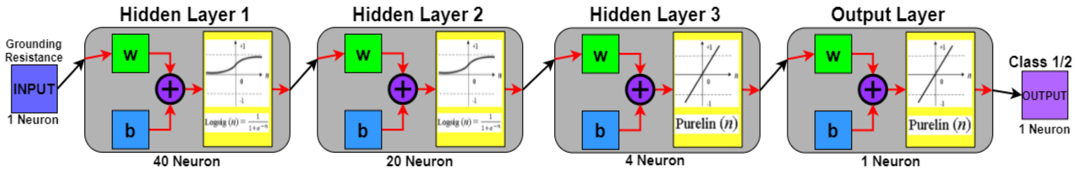


Figure 3. *ANN structure used in classification.*

Table 1. *Model Parameters*

Parameters	**Values/Types**
Adapt Function	'adaptwb' (Adapt network with weight and bias learning rules)
Activation Functions	'logsig', 'logsig', 'purelin'
Epochs	10000
Hidden Layers (HL)	3
HL Neurons	40,20,4
Performance Function	'mse' (Mean Squared Error)
Train Function	'traingdx' (Gradient Descent with Momentum and Adaptive Learning Rate)

4. Discussion and Results

Regression analysis is frequently used to describe the relationship between more than one variable and determine how effective the relationship between variables is. In the study, the classification process with ANN was made by analogy with the regression problems. Here, dry and stony soil is labeled 1, wet and stone-free soil 2. Therefore, regression analysis was used to define the relationship between soil structure and grounding resistance. The regression curves obtained as a result of the training and tests applied are given in **Figure 4**.

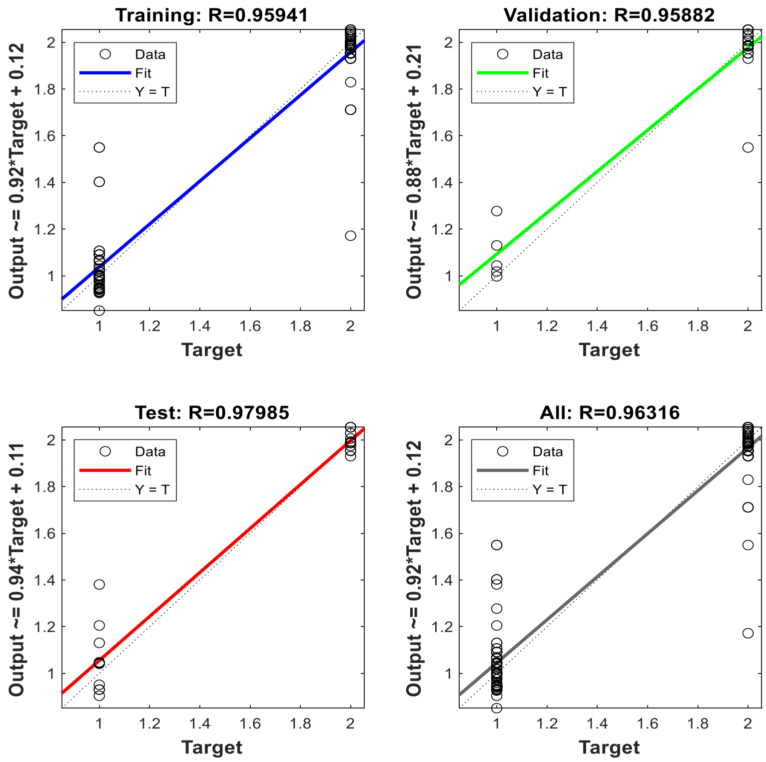


Figure 4. *The regression curve*

As can be seen from the curves formed, there is a strong relationship between the variables. When training, testing, and validation results are correlated in classification accuracy, the correlation coefficient (R) is over 0.9. Again, with the same results, when the mean square error (MSE) was calculated, very low values such as 0.014 were obtained in **Figure 5.**

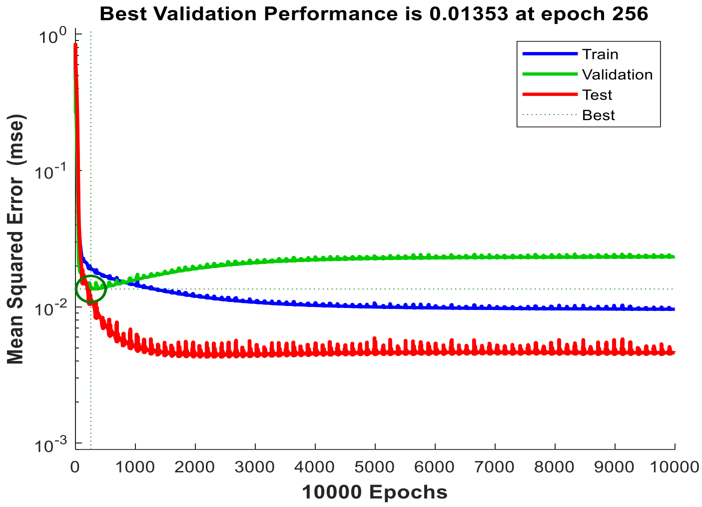


Figure 5. *Training, test, and validation MSE*

Therefore, the classification process is very efficient in training, testing, and validation. In addition, **Figure 6** presents a graph showing the gradient curve, the validation checks, and the adaptive learning rate used during training, which are among the network parameters.

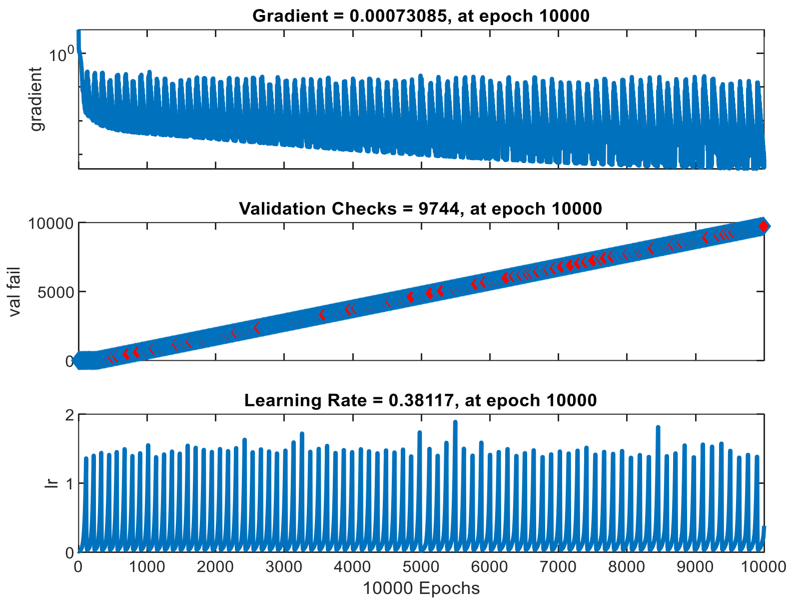


Figure 6. *Change in network parameters during training*

The applied classification test was performed on 40 random data that were not trained in the network structure before. The first group expresses the dry and stony soil structure in the classification, while the second group expresses the wet and stone-free soil structure. As a result of the tests, only 1 out of 40 data was classified incorrectly. Numerical Accuracy (3) and Mean Absolute Error (4) equations were used for performance evaluation as a result of training and testing.

$$\text{Accuracy (\%)} = 100 \times \left[1 - \left|\frac{(\text{Target} - \text{Output})}{\text{Target}}\right|\right] \quad (3)$$

$$MAE = \frac{\sum(Target - Output)}{Number\ of\ Test\ Data} \quad (4)$$

Therefore, the classification error is around 2.5%. The classification performance results of the data set used as test data are given in **Table 2**. Values with incorrect classification are marked in bold.

Table 2. *Classification Performance*

#	Test Input Data (Ωm)	Test Output Data (1/2)	Numerical Output	Numerical Accuracy %	Absolute. Error	Prediction of ANN	Classification
1	16	1	1.1303	86.97	0.13031	1	Dry-Stone
2	77	1	0.9471	94.71	0.05291	1	Dry-Stone
3	**15**	**2**	**1.1717**	**58.6**	**0.82828**	**1**	**Wet-Stoneless**
4	1	2	1.9866	99.33	0.01338	2	Wet-Stoneless
5	45	1	1.0913	90.87	0.09131	1	Dry-Stone
6	36	1	1.0034	99.66	0.00341	1	Dry-Stone
7	17	1	1.0909	90.91	0.09094	1	Dry-Stone
8	1	2	1.9866	99.33	0.01338	2	Wet-Stoneless
9	51	1	0.8508	85.1	0.14915	1	Dry-Stone
10	5	2	1.9829	99.15	0.01706	2	Wet-Stoneless
11	2	2	1.9522	97.61	0.04777	2	Wet-Stoneless
12	0.7	2	2.0062	99.69	0.00617	2	Wet-Stoneless
13	0.9	2	1.9927	99.63	0.00733	2	Wet-Stoneless
14	0.1	2	2.0544	97.28	0.05437	2	Wet-Stoneless
15	9	2	1.7112	85.56	0.28883	2	Wet-Stoneless
16	6	2	1.9723	98.62	0.02766	2	Wet-Stoneless
17	1	2	1.9866	99.34	0.01338	2	Wet-Stoneless
18	22	1	0.9333	93.33	0.06672	1	Dry-Stone
19	17	1	1.0909	90.91	0.09094	1	Dry-Stone
20	0.2	2	2.0459	97.71	0.04594	2	Wet-Stoneless
21	34	1	1.0574	94.26	0.05743	1	Dry-Stone
22	21	1	0.9511	95.11	0.04888	1	Dry-Stone
23	1	2	1.9866	99.33	0.01338	2	Wet-Stoneless
24	70	1	1.0017	99.83	0.00170	1	Dry-Stone
25	3	2	1.9540	97.67	0.04602	2	Wet-Stoneless
26	26	1	1.0183	98.17	0.01834	1	Dry-Stone
27	0.4	2	2.0293	98.53	0.02931	2	Wet-Stoneless
28	42	1	0.9593	95.93	0.04066	1	Dry-Stone
29	23	1	0.9429	94.3	0.05706	1	Dry-Stone
30	4	2	1.9740	98.7	0.02601	2	Wet-Stoneless
31	35	1	1.0411	95.9	0.04108	1	Dry-Stone
32	318	1	1.2393	76.1	0.23929	1	Dry-Stone
33	6	2	1.9723	98.62	0.02766	2	Wet-Stoneless
34	0.1	2	2.0544	97.3	0.05437	2	Wet-Stoneless
35	0.4	2	2.0293	98.53	0.02931	2	Wet-Stoneless
36	4	2	1.9740	98.7	0.02601	2	Wet-Stoneless
37	18	1	1.0684	93.2	0.06840	1	Dry-Stone
38	82	1	0.9262	92.62	0.07380	1	Dry-Stone
39	25	1	1.0043	99.57	0.00433	1	Dry-Stone
40	2	2	1.9522	97.61	0.04777	2	Wet-Stoneless
Average Numerical Accuracy = %94.61					**MAE = 0.07**	**Avg. Class. Error = %2.5**	

5. Conclusions and Future Work

Grounding systems, which must be used as the primary measure in protecting electrical installations, are a vital issue in electrical engineering regarding pre-feasibility studies, operations during installation, and post-installation reliability. The nonlinear variation of the soil contact resistance according to the soil type plays an essential role in determining the grounding resistance with the theoretical mathematical formulas, especially in the pre-feasibility studies of the grounding systems established in rocky and sandy areas. In addition, it becomes difficult to predict and follow the behavior of the grounding resistance after installation. Therefore, a grounding system must provide a low resistance path to fault current, protect living things from electric shocks caused dangerous steps and touch voltages, and reduce damage to electrical equipment.

In this study, experimental measurements were made with a measuring instrument based on the Wenner Method according to soil types, and a data set regarding soil resistance values was created. This data set was trained in MLP type ANN network, and classification was made between grounding resistances. The soil types depending on the grounding resistance were mainly determined with the classification process. Classification error is around 2% in tests performed with samples taken out of the data set. The error rate of the proposed approach is close to the error rates of simple soil structures in the literature. Since the experimental measurements made within the scope of this study belong to very complex soil structures, the success rate obtained is relatively sufficient. Therefore, the estimations to be made with artificial intelligence methods before going to the field to determine grounding resistance provide significant benefits in terms of cost and time. Moreover, the proposed general classification algorithm approach can be applied to any grounding system according to the data set based on experimental measurements. In future studies, to determine the behavior of the grounding systems of wind power plants, which are generally established in rocky areas, under different meteorological conditions, a study including long-term measurements at certain intervals can be carried out.

Acknowledgments

We would like to thank the company "Karaman Akar Mühendislik Sanayi ve Tic. Ltd. Şti / Karaman/Turkey" for supporting the experimental studies within the scope of university-industry cooperation for the measurement of grounding resistance.

Declaration of interest

This article was presented as orally at the ICAIAME 2021 conference.

References

[1] Balcı S, Helvacı, ÖA. "Comparative simulation on the grounding grid system of a wind turbine with FEA software", *Journal of Energy Systems* (2019) 148–157.

[2] "ANSI/IEEE Std 81-1983", IEEE Guide for Measuring Earth Resistivity, Ground Impedance, and Earth Surface Potentials of a Ground System (1983).

[3] Asimakopoulou FE, Kourni EA, Kontargyri VT, Tsekouras GJ, Stathopulos IA. "Artificial neural network methodology for the estimation of ground resistance", In Proc. 15th WSEAS International Conference on Systems (2011, July) 453–458.

[4] "EN 62561-7:2012", Lightning Protection System Components (LPSC) – Part 7: Requirements for earthing enhancing compounds (2012, Jan.).

[5] Androvitsaneas VP, Gonos IF, Dounias GD, Stathopulos I. "Ground resistance estimation using inductive machine learning", In 19th Int. Symp. High Voltage Engineering (2015, August). Pilsen, Czech Republic.

[6] Asimakopoulou FE, Tsekouras GJ, Gonos IF, Stathopulos IA. "Artificial neural network approach on the seasonal variation of soil resistance", In 2011 7th Asia-Pacific International Conference on Lightning (2011, November). 794–799; doi: 10.1109/APL.2011.6110235.

[7] Boulas K, Androvitsaneas VP, Gonos IF, Dounias G, Stathopulos IA. "Ground resistance estimation using genetic programming", In Proc. 5th Int. Symp. 27th National Conf. Operational Research (2016, June) 66–71. Greece, Athens.

[8] Androvitsaneas VP, Asimakopoulou FE, Gonos IF, Stathopulos IA. "Estimation of ground enhancing compound performance using artificial neural network", In 2012 International Conference on High Voltage Engineering and Application (2012, September) 145–149; doi: 10.1109/ICHVE.2012.6357068.

[9] Androvitsaneas VP, Gonos IF, Stathopulos IA, Alexandridis AK, Dounias G. "Wavelet neural network for ground resistance estimation", In 2014 ICHVE International Conference on High Voltage Engineering and Application (2014, September) 1–5; doi: 10.1109/ICHVE.2014.7035419.

[10] Denche G, Faleiro E, Asensio G, Moreno J. "An Estimator of the Resistance of Large Grounding Electrodes from Its Geometric Characterization", *Applied Sciences* 10(22) (2020) 8162; doi: 10.3390/app10228162.

[11] Kondylis GP, Damianaki KD, Androvitsaneas VP, Gonos IF. "Simplified formulae method for estimating wind turbine generators ground resistance", *IEEE Transactions on Power Delivery* 33(6) (2018) 2829–2836; doi: 10.1109/TPWRD.2018.2839061.

[12] Androvitsaneas VP, Alexandridis AK, Gonos IF, Dounias GD, Stathopulos IA. "Wavelet neural network methodology for ground resistance forecasting", *Electric Power Systems Research* 140 (2016) 288–295; doi: 10.1016/j.epsr.2016.06.013.

[13] Faleiro E, Asensio G, Moreno J. "An estimate of the uncertainty in the grounding resistance of electrodes buried in two-layered soils with non-flat surface", *Energies* 10(2) (2017) 176; doi: 10.3390/en10020176.

[14] Asimakopoulou FE, Kontargyri VT, Tsekouras GJ, Gonos IF, Stathopulos IA. "Estimation of the earth resistance by Artificial Neural Network model", *IEEE Transactions on Industry Applications* 51(6) (2015) 5149–5158; doi: 10.1109/TIA.2015.2427114.

[15] İlisu İÖ, "Grounding Against Indirect Touch in Electrical Facilities", Chamber of Electrical Engineers Continuing Education Center (EMO) EG/2010/1.

[16] Salam MA, Rahman QM, Ang SP, Wen F. "Soil resistivity and ground resistance for dry and wet soil", *Journal of Modern Power Systems and Clean Energy* 5(2) (2017) 290-297.

[17] Zupan J. "Introduction to artificial neural network (ANN) methods: what they are and how to use them", *Acta Chimica Slovenica* 41 (1994) 327–327.

[18] Uhrig RE. "Introduction to artificial neural networks", In Proceedings of IECON'95-21st Annual Conference on

IEEE Industrial Electronics 1 (1995, November) 33–37. IEEE.

[19] Kayabasi A, Yildiz B, Aslan MF, Durdu A. "Comparison of ELM and ANN on EMG signals obtained for control of robotic-hand", In 2018 10th International Conference on Electronics, Computers and Artificial Intelligence (ECAI) (2018, June) 1–5. IEEE.

[20] Yılmaz I, Yuksek AG. "An example of artificial neural network (ANN) application for indirect estimation of rock parameters", *Rock Mechanics and Rock Engineering* 41(5) (2008) 781–795.

[21] Benghanem M, Mellit A, Alamri SN. "ANN-based modeling and estimation of daily global solar radiation data: A case study", *Energy conversion and management* 50(7) (2009) 1644–1655.

[22] Anuradha B, Reddy VV. "ANN for classification of cardiac arrhythmias", *ARPN Journal of Engineering and Applied Sciences* 3(3) (2008) 1–6.

[23] Kumar V, Sachdeva J, Gupta I, Khandelwal N, Ahuja CK. "Classification of brain tumors using PCA-ANN", In 2011 world congress on information and communication technologies (2011, December) 1079–1083. IEEE.

[24] Abiodun, OI, Jantan A, Omolara AE, Dada KV, Mohamed NA, Arshad H. "State-of-the-art in artificial neural network applications: A survey", *Heliyon* 4(11) (2018) e00938.

[25] Abiodun OI, Jantan A, Omolara AE, Dada KV, Umar AM, Linus OU, ... Kiru MU. "Comprehensive review of artificial neural network applications to pattern recognition", *IEEE Access* 7 (2019) 158820-158846.