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Research Article

Development of a Machine Learning Based Clinical Decision Support System for Classification of Migraine Types: A Preliminary Study

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Abstract – Migraine is a type of neurological headache that seriously affects daily life and is associated with different symptoms. Early diagnosis of migraine disease is important for the start of the treatment process. In this process, specialized physicians are always needed, but artificial intelligence-based clinical systems can save time in the diagnosis of migraine and other headache types and can help determine the right treatment methods by providing support to general practitioners. In this study, the classification of migraine typical with aura and migraine without aura, which are the most common types of migraine, and other types of migraine were performed. In the classification process, data from demographic and clinical questionnaires were used and five different machine learning models were applied. In this research, the Rotation Forest algorithm showed the most successful performance according to the classifier evaluation criteria. As a result of this algorithm, accuracy (95.14%), true positive (95.10%), false positive (2.40%), kappa statistics (92.71%) and mean absolute error (6.50%) rates were obtained.

Keywords – Neurological Headache, Migraine, Machine Learning, Classification, Clinical Decision System.

I. INTRODUCTION

Migraine is a neurological disorder that affects 11% of the world population and is characterized by recurrent headaches [1, 2]. Migraine is generally associated with nausea, and light and sound sensitivity and there is little consensus on the etiology of migraine. Migraine is a type of headache consisting of various subtypes [3]. The International Headache Society committee categorizes migraine into subtypes according to symptoms [4]. The most common types are migraine typical with aura (mtwa) and migraine without aura (mwa) [3, 5]. Apart from these types, there are other types such as migraine with brainstem aura, status migraine, sporadic hemiplegic migraine (shm), and familial hemiplegic migraine (fhm) [5]. There may be similarities and differences between migraine types according to various symptoms [6]. Mwa is a severe headache that is usually felt unilaterally with nausea, sound, and light sensitivity [4]. Mtwa, also known as complicated migraine, may show some symptoms related to visual impairment, and sensory and speech before migraine attacks [4, 5, 7]. Other types of migraine may vary depending on genetic factors or drug use and are less common than migraine with and without aura [8.

Migraine is a neurological disorder that is treatable over time once diagnosed but still lacks clear and easy diagnostic biomarkers. The diagnosis of migraine and headaches is too comprehensive to be solved in one go. If the treatment process is not started, migraine can cause significant problems in daily life. For this reason, early diagnosis of migraine or its subtypes is important. It is difficult to find a simple way to treat migraine patients, so it is important to identify response biomarkers and rapid diagnosis of the disease [9]. It is seen that different studies have been carried out recently to diagnose migraine or to distinguish its subtypes from each other. In some of these studies, neuroimaging techniques such as Electroencephalography (EEG), Magnetic resonance imaging (MRI), and Functional magnetic resonance imaging (fMRI) were used [8-12]. However, it is important to develop systems that can save time and cost and provide information to the general practitioner and clinician at the pre-diagnosis stage without the need for these imaging methods.

Recently, it has been seen that studies on the development of artificial intelligence-based clinical decision support systems (CDSS) in the field of healthcare are important [13, 14]. Today, artificial intelligence is applied in many fields besides medicine and healthcare and has become an important power [15]. With the use of artificial intelligence in medicine and health services, support can be provided to physicians and rapid diagnosis of diseases can be provided depending on physician knowledge [9, 16, 17]. In the studies, ML methods, a sub-branch of artificial intelligence, are used in optimization processes or classification phases [18]. Artificial intelligence for medical decision support systems has recently been used in migraine diagnosis and as a predictor of the results of migraine treatments. Among these, promising results have also been observed [16]. In such studies, predictions on disease diagnosis are made using machine learning (ML) or deep learning (DL) models from artificial intelligence models using data obtained from clinical tests or some survey questions [4, 5, 9].

It was mentioned above that studies have been conducted on the diagnosis of migraine or the determination of migraine types using imaging methods. However, before applying imaging methods, artificial intelligence-based studies that can quickly inform the physician about the disease and save time with clinical tests or questionnaire-based data obtained in the form of a question-answer between the patient and the physician are described below.

- In addition to migraine diagnosis based on clinical survey data, there are studies examining the relationship between migraine and drug use. In the examined study, migraine classification was performed using a machine learning model, and migraine and drug use were predicted [2].

- In another study on the determination of migraine types, Jalannavar et al. examined clinical survey data with deep learning models. As a result of their study, certain data were used as features, and migraine types were classified [4].
- Gulati et al. performed the classification of seven migraine types using five supervised machine learning models. They used survey-based data in the classification process. As a result of the classification process, they determined the most appropriate classifier as Naive Bayes (NB) [5].
- Sasaki et al. proposed an artificial intelligence model for the diagnosis of migraine disease in pediatric and adolescents using survey datasets. Using 909 records, the proposed model was analyzed with accuracy, sensitivity, and specificity criteria [19].
- In a study on the classification of migraine types and headache types, Han et al. designed a clinical decision support system. In their design, 653 records were analyzed and data from physician-patient interviews conducted via mobile devices were used [20].

Despite the studies mentioned above, it is stated that there is a lack of artificial intelligence-based studies on migraine diagnosis and determination of migraine types, and more research is needed [5, 9-11]. In this study, a preliminary study is proposed for the development of CDSS for migraine diagnosis and identification of migraine subtypes. The proposed study aims to contribute to the literature on the development of CDSS that can help general practitioners, clinicians, and migraine patients by using machine learning algorithms, which is a sub-model of artificial intelligence, and to eliminate the lack of studies. For this purpose, mtwa and mwa, which are the most common types of migraine, and other types of migraine were classified using survey-based data. The classification process was performed using 5 different machine learning methods. In order to perform fast and effective classification, important features in the data set were determined and the classification process was carried out. Detailed information about the realization of these processes and the data structure used are described in Section 2. In Section 3, the results obtained and the discussion of these results are mentioned. In the last section, the study is concluded and an evaluation is made of future studies.

II. METHODOLOGY

This research, it is aimed to contribute to the studies of computer-aided clinical decision systems that enable the most common migraine types, mtwa, and mwa, to be distinguished from other migraine types by using machine learning methods, which is a sub-branch of artificial intelligence. For this purpose, in the preliminary stage of the diagnosis of the disease, the classification process was carried out by using the answers given to a number of questions posed by the physician to migraine patients as features. Before the classification process, the feature selection process was applied due to its effect that can speed up the classification process and increase its performance. In the classification process, 3 different groups were used mtwa, mwa, and other types. Since the data records of these 3 groups showed an unbalanced distribution, data balancing was performed in the pre-processing stage in order to interpret the results more accurately. Classification results were analyzed by obtaining Accuracy (ACC), true positive rate (TPR), false positive rate (FPR), kappa statistic (KAPPA), and mean absolute error (MAE) rates. The flow diagram for the study is shown in Figure 1.

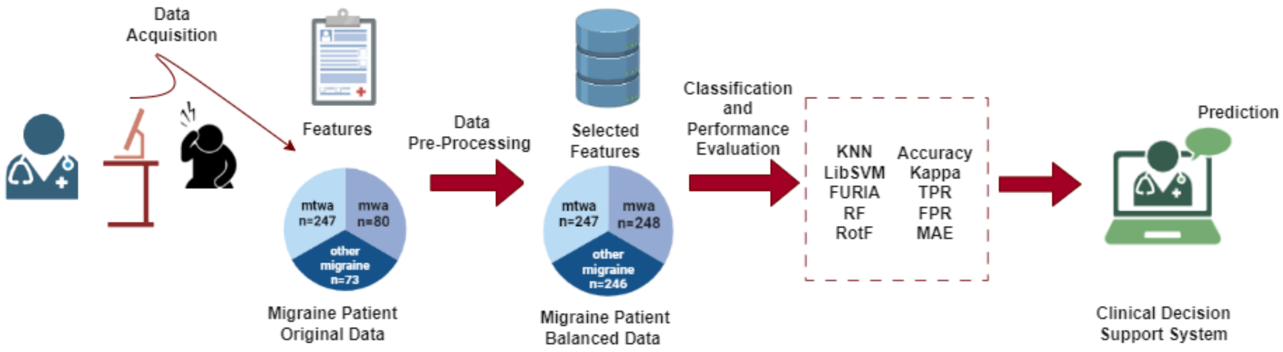


Figure 1. Flowchart of this study

2.1 Data set

The dataset used in this study was obtained from the Kaggle platform, which provides open-access data sharing for machine learning studies [21]. The dataset used consists of 400 migraine patient records. Of the 400 migraine patients diagnosed by a physician, 247 are mtwa, 80 are mwa and 73 are other migraine types (shm, fhm, other migraine). The data set used in the research contains 23 features. These characteristics consist of the answers obtained by asking clinical questions to migraine patients during the pre-diagnosis stage the physician and age information. These questions consist of information about the duration and frequency of headaches, reactions to sound and light, and some symptoms seen in the body. Information about the data set in the study before the pre-processing phase is given in Table 1. In the study, important features were selected using the feature selection method, and data balancing was performed before the classification process. These stages are mentioned in the preprocessing stage in section 2.2.

Table 1. Data set information in the study before the pre-processing phase

Migraine Type	**Features**
• Migraine typical with aura (n=247) • Migraine without aura • (n=80) • Other Migraine (n=73)	• Age / Duration / Frequency • Location / Character / Intensity • Nausea / Vomit / Visual • Dysphasia / Dysarthria • Phonophobia / Photophobia/ Sensory • Vertigo / Tinnitus / Hypoacusis • Diplopia / Defect / Ataxia • Conscience / Paresthesia / DPF

2.2 Data pre-processing

The data to be used in the classification process may sometimes contain missing values or unbalanced distributions may occur in the data. In order to organize these missing values and eliminate data imbalances, the data preprocessing stage should be performed. Data preprocessing is the processing of raw input data and applying appropriate transformations to the data for the best results [17]. In this study, there is no data containing missing values. However, some adjustments were made to the data before the classification stage. The data set information used in the study after the preprocessing is given in Table 2.

Feature selection is a technique that defines subsets of the original features and selects meaningful features from them in order to improve the performance and efficiency of classification models. In this study, the Information Gain (IG) algorithm, one of the feature selection methods, was used to select meaningful features. The IG technique calculates the reduction in entropy resulting from the transformation of a dataset. The entropy of each variable is evaluated in the context of the target variable and used for feature selection [22]. In this research, as a result of the feature selection process, 23 features in the original data were reduced to 11.

Due to the unbalanced distribution of the data before the classification stage, data balancing was applied in the pre-processing stage to over-sample the minority classes. In this study, the Synthetic Minority Over-Sampling Technique (SMOTE) method, which is frequently preferred in studies, was applied in the data balancing process. SMOTE is a technique applied for data balancing. It produces synthetic samples for minority classes and equalizes the number of data for the majority class [23]. Performing the classification process with an unbalanced distribution of data is not suitable for accurate interpretation of prediction results [23, 24]. The original data used in the study consists of 400 migraine patient records. Of these, 247 were mtwa, 80 were mwa and 73 were other migraine patients. In this study, the mwa data, which was 80 before the balancing process, was increased to 248 and the other migraine data, which was 73, was increased to 246. Thus, the number of data used before the classification process was increased to 741. Classification was also performed using the data to which the SMOTE technique was not applied. Classification results were obtained with the unbalanced and balanced data and the performances of the models were compared in the results discussion section in Section 3.

Table 2. Data set information after the pre-processing

Migraine Type	**Features**
• Migraine typical with aura (n=247) • Migraine Without Aura (n=248) • Other Migraine (n=246)	• Age/ Frequency • Location / Character • Intensity / Vomit • Visual / Sensory • Vertigo / Tinnitus • DBF

2.3 Classification and Performance Evaluation

Classification is the process of distributing the data into classes in a controlled manner after passing through the training and testing phase. In machine learning processes, the classification phase consists of two parts: training and testing. The data set in the training phase is given as input to the learning algorithm that learns how to predict the outputs. The testing phase involves determining the prediction performance of the learning algorithm on previously unseen examples from the test dataset [17]. These processes are performed using the Cross-validation technique used to evaluate machine learning models. In this study, the original data set was set as CV=10 with 90% training and 10% test data, and the classification process was performed. Fuzzy Unordered Rule Induction Algorithm (FURIA), K-Nearest Neighbour (KNN), Random Forest (RF), LibSVM, and Rotation Forest (RotF) were preferred in the classification process.

The Fuzzy Unordered Rule Induction Algorithm is an improved version of the RIPPER algorithm. In this model, fuzzy rules and a new rule expansion technique are used instead of traditional rules. It has been observed to perform well compared to similar models [23].

K-Nearest Neighbour is a supervised model applied in many areas of machine learning studies. It uses different search algorithms and distances to determine the nearest neighbor in the feature space [23].

In the Random Forest algorithm, multiple random trees are generated in the subspace of the feature space. Depending on the strength and correlation of these trees, errors can be obtained [23]. It is a successful ML model preferred in both classification and regression studies [5].

LibSVM is known as a library of support vector machine (SVM) algorithms. It is a model developed by complementing some parameters of the SVM algorithm. In this algorithm, a hyperplane is usually used to solve the two-class problem by distinguishing between positive and negative examples [25].

Rotation Forest is a tree-based classification method similar to RF and Bagging. It has an extra parameter that controls the size or number of feature subsets. The most important feature of the Rotation Forest model is that it combines the principal component analysis method with the C4.5 decision tree algorithm [26].

Brief information about the classifiers used in this research has been mentioned above. The performances of the classifiers were evaluated using Accuracy, TPR, FPR, kappa statistics, and MAE metric results. The accuracy rate is calculated as the rate of the data correctly predicted by the model to the whole dataset. Kappa statistic measures the agreement between classifiers. A Kappa statistic value greater than 0.75 indicates that the consistency of the classifier is good. It is stated that a large TPR and a small FPR are good for the classification process [27]. In the studies, these criteria are calculated by using True Positives (tp), True Negatives (tn), False Positives (fp), and False Negatives (fn) values which are the indicators of the confusion matrix.

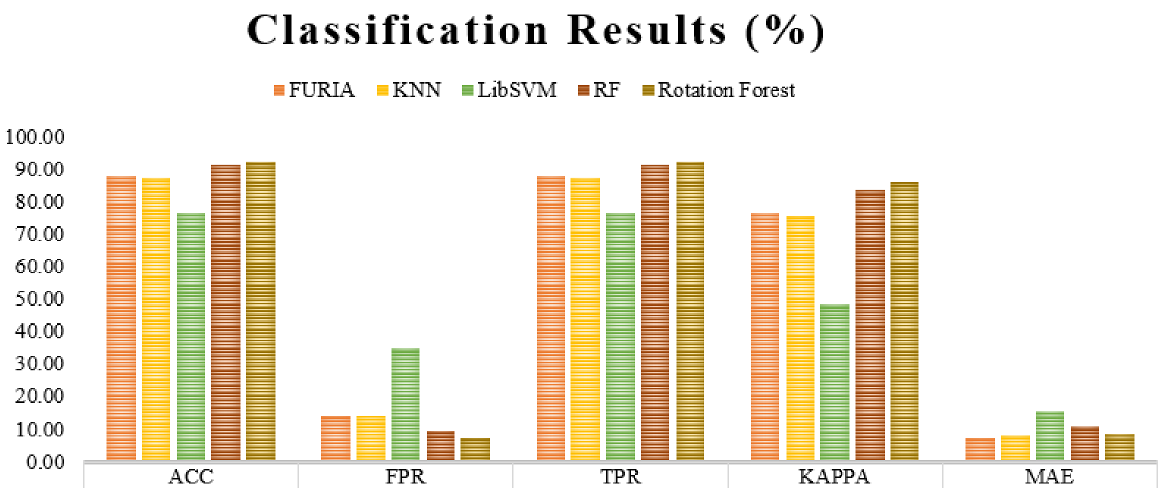
$$\boldsymbol{Accuracy} = \frac{tp+tn}{tp+tn+fp+fn} \tag{1}$$

$$\mathbf{FPR} = \frac{fp}{tn+fp} \tag{2}$$

$$\mathbf{TPR} = \frac{tp}{tp+fn} \tag{3}$$

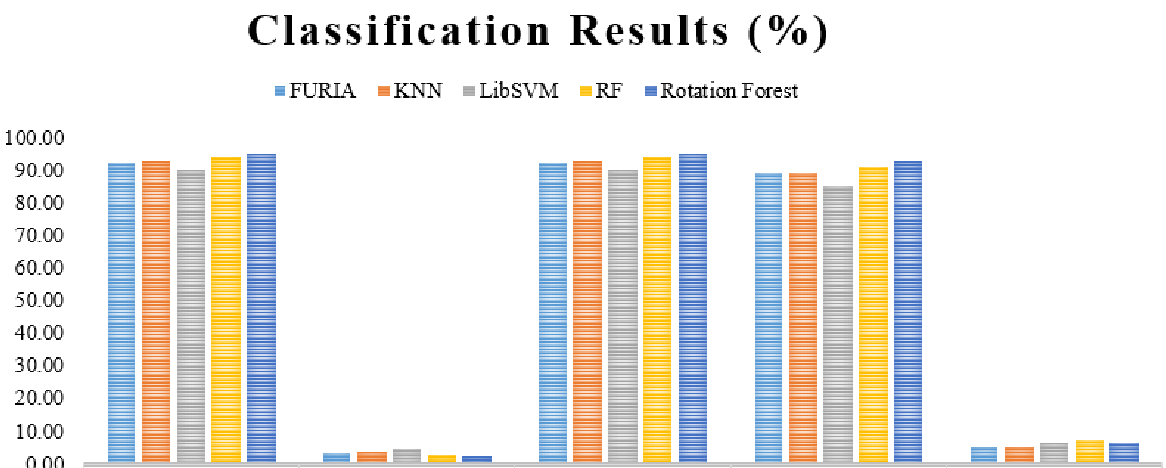
III. RESULT AND DİSCUSSİON

In this study, it is aimed to develop a CDDS that can help physicians in the diagnosis and determination of the type of migraine disease. For this purpose, the most common types of migraine, mtwa, and mwa, as well as other types, were classified using machine learning algorithms. Before the classification process, the pre-processing stage was performed important features were determined with the (IG) algorithm, and a balanced distribution of the data was ensured with the SMOTE process. After the balanced distribution, the total number of data was 741, including 247 mtwa, 248 mwa, and 246 other migraine types classes. In the classification process, the data set was divided into 10 equal parts by applying 10-fold cross-validation. 90% of the data was used for training (667 records) and 10% (74 records) was used to train the models. In the classification process, FURIA, KNN, RF, LibSVM, and Rotation Forest models were preferred. At the end of the classification process, Accuracy, TPR, FPR, kappa statistics, and MAE metric results were obtained and the performances of the classifiers were evaluated to determine the most appropriate model. The results of the classifier models obtained from the original data set before the SMOTE process are shown in Figure 2. The classification results obtained by applying the SMOTE technique to the data are shown in Figure 3.



	ACC	FPR	TPR	KAPPA	MAE
FURIA	87.75	14.30	87.80	76.55	7.50
KNN	87.25	14.00	87.30	75.75	8.53
LibSVM	76.50	35.20	76.50	48.62	15.67
RF	91.50	9.90	91.50	83.90	10.90
Rotation Forest	92.50	7.60	92.50	86.00	8.85

Figure 2. Classification Results of the Original Data Set



	ACC	FPR	TPR	KAPPA	MAE
FURIA	92.85	3.60	92.80	89.28	5.20
KNN	92.85	3.60	92.80	89.28	5.10
LibSVM	90.28	4.90	90.30	85.42	6.50
RF	94.10	3.00	94.10	91.10	7.50
Rotation Forest	95.14	2.40	95.10	92.71	6.50

Figure 3. Classification Results of the Data Set with SMOTE

There are studies on the classification of migraine types by applying ML and DL models using the data type in this study [4, 5, 28]. However, in these studies, it is seen that the data are evaluated by showing an unbalanced distribution in their original form. In this case, it is thought that it would not be appropriate to interpret the classification results in a healthy way [23, 24]. In addition, in the studies conducted in the literature, it was observed that important features were not determined and used in their original form [4, 28].

In this study, unlike the studies in the literature, unimplemented classifier models were preferred important features were determined in the pre-processing stage and the data were balanced. It was observed that balancing the data and identifying important features improved the classification results. In this study, the classification process was carried out with the data in its original form and balanced distribution (Figure 2-

3). Looking at the results in Figures 2 and 3, it was seen that performing the SMOTE process increased the performance in classification results. It may be more appropriate to evaluate the results of this research according to the results in Figure 3. According to the metric results evaluated in the research given in Figure 3, the classifier model showing the most successful performance is the Rotation Forest algorithm. The contributions of this study to the literature are as follows:

1. It is seen that the results obtained from the Rotation Forest algorithm improve the results in studies on the identification of migraine types using similar data structures [5, 19, 28].

2. According to Chawla et al., the interpretation of the results obtained with balanced data is more favorable than unbalanced data results [24]. In this study, the results obtained with the data balancing process were compared with the results obtained from the original data. The results obtained with balanced data, which we think can be interpreted more accurately, have shown more successful performance.

3. Artificial intelligence-based CDSS studies are important in the fields of medicine and health [15]. This research can contribute to AI-based CDSS studies for early diagnosis of neurological disorders such as migraine and the lack of studies in the literature.

The research has some limitations and these limitations are as follows.

1. The fact that there are few studies using similar data structures and the comparison with the results of this study is insufficient.

2. The small number of data used in the research for the development of CDSS. This research can be seen as a preliminary study. In the future, research on migraine diagnosis should be carried out by increasing the number of data in this study and supporting it with clinical measurement data.

IV. CONCLUSION AND FUTURE RESEARCH

Artificial intelligence-based studies can provide support, especially to non-specialist physicians in the field, enabling early diagnosis of diseases and prompt initiation of treatment, thereby preventing unnecessary drug exposure. Additionally, the development of Clinical Decision Support Systems (CDSS) through such studies can reduce healthcare costs and save time in diagnosis and treatment. Through artificial intelligence, migraine diagnosis can be made based on questionnaire data, and differentiation of other types of headaches can be achieved. In this research, significant features for the classifier were identified from the data obtained from the questionnaire, and machine learning models were applied to classify migraine types. The results shown in Figure 3 are promising for future research. High rates of Accuracy, True Positive Rate (TPR), and kappa statistics, along with low rates of False Positive Rate (FPR) and Mean Absolute Error (MAE), are desirable for prediction and classifier performance. We believe that this research can contribute to the literature on the detection of migraine and its types. However, there are gaps in research on migraine diagnosis and classification of migraine types, indicating the need for further investigation. The literature gap on early detection of migraine and other neurological diseases can be addressed through future studies by increasing the number of data and diversity of features, facilitating the development of AI-based CDSS capable of diagnosing diseases. While we acknowledge the necessity of specialist physicians in disease diagnosis, AI-based CDSS can provide preliminary information to clinicians without the need for EEG or other imaging methods, assisting in the diagnosis of migraine disease.

DECLARATİON OF COMPETİNG INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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