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Prediction Accuracy of Eye-Open State using WEKA Algorithms

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Abstract
Purpose: Brain diseases are reflected in the pattern of brain-waves recorded using electroencephalography (EEG). We aimed to evaluate the prediction accuracy of machine learning algorithms embedded in WEKA software tool applied to the EEG eye-state signal dataset. **Methods**: The eye-state dataset was retrieved from UCI ML repository, and it consists of 14980 samples (instances), 15 attributes (electrodes), and each instance was one continuous EEG measurement made within 117 seconds. The two classes in the dataset are '1', indicating the eye-closed state and '0' the eye-open state. The prediction accuracy of eye-closed and eye-open was done with machine learning algorithms incorporated in WEKA software tool. **Results**: The best statistical performance evaluation measure was observed in this study for the classifiers viz., Random Forest, Random Tree, J48, Bagging and Decision table. Random Forest predicted the edited test dataset in the ratio of 7:3 (correct : incorrect). **Conclusion**: Among the five classifiers, Random Forest and Bagging gave significant performance ('v') while analyzed in the 'experimenter' environment in WEKA.

Keywords: Waikato Environment for Knowledge Analysis (WEKA); EEG (electroencephalography) eye-state dataset; Machine Learning; Classifiers; Random Forest

Introduction

The electroencephalograph (EEG) is a biomedical device that creates a graph that measures brain-waves known as electroencephalogram. The EEG device is the most frequently used to identify pathological conditions that cause abnormal EEG readings, such as brain death, encephalopathies, coma, sleep, dream, epilepsy etc. The EEG is used for diagnosing tumors, strokes, and other localized brain diseases [1], and the EEG recordings are useful for several neurological and behavioral applications [2] such as dementia, attention deficit hyperactivity disorder, Alzheimer's diagnosis, traumatic brain injury, encephalitis and psychiatric disorders.

The ability to classify and predict brain activity from plugged electrode recording data is gaining more and more importance with the development of brain-computer interface technology. The occurrence of eye movements either as close (1) or open (0) determines the EEG pattern and consequent distortions in the brain waves [3]. As EEG is related to the ocular state with brain-wave spikes, its classification is crucial [4], and hence the EEG signals are used as research input data [5]. The pattern of EEG recordings is a tool for brain-computer interfaces (BCI) [5]. Thus, EEG eye-state categorization is an utmost importance in research and diagnosis [6, 7]. The EMOTIV headset is a tool that provides numerical value and corresponding brain wave peaks [8].

The Waikato Environment for Knowledge Analysis (WEKA) provides access to cutting-edge machine learning techniques for data mining researchers across the disciplines, and it is a groundbreaking system in data mining and machine learning [9]. Machine learning (ML), an area of artificial intelligence (AI), enables researchers, physicians, and patients to solve specific tasks instantly [10]. WEKA is a non-code implemented ML suit [11], embedded with machine learning classifier algorithms. For simulation purposes, WEKA Data Mining tool can be utilized [12], and several visualization tools and algorithms for data analysis and predictive modelling are included in the WEKA workbench, together with graphical user interfaces allowing quick access to these capabilities [13].

The neurons in the brain depolarize, generate and communicate electric impulses upon stimulus. These impulses appear as wavy lines in EEG recordings. There are several sensory stimuli that influence the impulses in the brain through pain, taste, touch, smell, auditory and optic receptors. Among these, the optic stimulus is unique in which the elicitation of arousal of brain function appears just by opening the eyes of an active subject. Hence, the eye-open and eye-closed states influence the EEG pattern (Figure 1). In a real-time system, it is possible to predict eye-states using EEG records with an accuracy ranging from about 96% to over 99% [14]. The intention focused in this article is to apply the machine learning (ML) algorithms included in WEKA workbench so as to assess statistically the best proven algorithm on EEG recordings and also the edited test dataset with a study hypothesis that the ML algorithms would provide a confidence on the reliability of EEG eye-states.

Material and Method

Awareness of neurological wellbeing of an individual is yet to be familiarized to the people at large. The brain-waves, normally recorded using EEG, at different behavioral states must be understood (Figure 1).

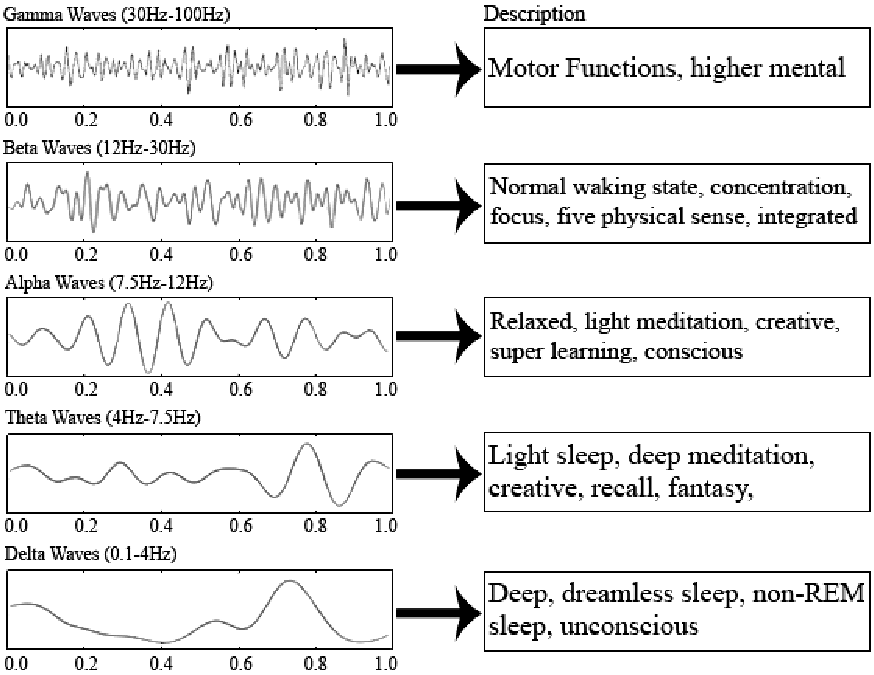

Figure 1. The brain-electrical wave pattern (EEG) classified based on the condition of a man is shown. (Source link: https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.researchgate.net%2Ffigure%2FBrain-wavesdescription_fig1_325701712&psig=AOvVaw0nrFx5S7Dgw7EsA8HrBhPZ&ust=1678603089091000&source=images&cd=vfe&ved=0CBAQjRxqFwoTCKibr_ih0_0CFQAAAAAdAAAAABAE).

The dataset on EEG eye-state was collected in ARFF (Attribute Related File Format) format from UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/datasets.php). This data set consists of 14980 instances and 15 attributes at specified locations on the skull namely AF3 – Anterior frontal, F7 - Left Frontal, F3 - Left Frontal, FC5 – Functional connectivity, T7 - Left Temporal, P7 - Left parietal, O1 - Left Occipital, O2 -Right Occipital, P8 - Right Parietal, T8 - Right Temporal, FC6 - Functional connectivity, F4 - Right Frontal, F8 - Right Frontal, AF4 - Anterior frontal, and Eye Detection. The dataset on EEG Eye-state contains two classes 0 (eye in open state) and 1 (eye in closed state). The test data set comprising of 10 instances was chosen randomly without processing from the UCI ML repository to observe the performance of the best classifier.

The WEKA (version 3.8.6) desktop software tool was downloaded and installed (https://weka.en.softonic.com/?ex=DINS-635.2). The collected EEG eye-state dataset was uploaded to WEKA software.

The Naive Bayes classifier was used in the Bayes folder. Multilayer Perceptron, SMO, and Voted Perceptron were employed in the current study from the Functions folder. Bagging, Logit Boost and Stacking classifiers were used in the Meta folder. Decision Table was used in the Rules folder. J48, Random Forest, and Random Tree were utilized in the Trees folder. The current study utilized a total of 11 classifiers.

The performance evaluation of the classifiers on EEG eye-state dataset was assessed under the heads namely Precision, Recall, F-Measure and Accuracy. The values for these parameters were derived using the formulae given in Table 1.

The performances of classifiers were tested with McNemar test (https://www.openepi.com/MatchCC/MatchCC.htm, Matched Pair Case-Control Study [21]).

Table 1. The formulae used to calculate the performance evaluation of the classifiers for the accuracy prediction.

S.No.	Parameter	Formula	Interpretation
1.	Precision	(TP/TP+FP)*100	This parameter measures the model's accuracy in classifying sample as positive.
2.	Recall	(TP/TP+FN)*100	This measure is a true positive rate.
3.	F-Measure	2*(Precision*Recall/Precision+Recall)	This measure combines Precision and Recall. It evaluates the performance of the chosen algorithm.
4.	Accuracy	(TP+TN/TP+TN+FP+FN)*100	This measure evaluates correct predictions given by the chosen algorithm in relation to the total number of predictions made.

TP:True Positive; TN:True Negative; FP:False Positive ; FN:False Negative

Results

The accuracy prediction and statistical parameters obtained using the classifiers are tabulated in Tables 2 and 3.

The Stacking, Multilayer Perceptron and Navie Bayes classifiers yielded the highest mean absolute error values viz., 0.4948, 0.4864 and 0.5346 (Table 3). The least time taken to build the model was obtained by the classifier namely Stacking, which ran within 0.06 seconds. Furthermore, the classifiers such as Random Tree and Navie Bayes ran within 0.08 seconds. The Bagging, Voted Perceptron, Decision Table, Random Forest and Multilayer Perceptron took the maximum time to build the model viz., 1, 1.05, 1.37, 4.08 and 9.29 seconds respectively. Multilayer Perceptron was used to analyse EEG non-linear separable datasets. The structure of MLP architecture (Figure 2) consisting of the input layer, two hidden layers and an output layer representing the 'class'. The two hidden layers showing the neural connections of input attributes with the neurons indicated that the EEG eye state dataset was non-linear separable.

The performances of classifiers are presented in Table 4.

Table 2. Detailed accuracy prediction of the classifiers by Class of the EEG Eye dataset from UCI ML Repository by the chosen classifiers in WEKA tool

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
Naive Bayes	0.141	0.140	0.553	0.141	0.224	0.001	0.509	0.559	0
	0.860	0.859	0.449	0.860	0.590	0.001	0.509	0.457	1
	0.464	0.463	0.506	0.464	0.388	0.001	0.509	0.513	Wt Avg.
SMO	1.000	1.000	0.551	1.000	0.711	0.009	0.500	0.551	0
	0.000	0.000	1.000	0.000	0.000	0.009	0.500	0.449	1
	0.551	0.551	0.753	0.551	0.392	0.009	0.500	0.505	Wt Avg.
Bagging	0.924	0.141	0.890	0.924	0.907	0.788	0.961	0.965	0
	0.859	0.076	0.903	0.859	0.880	0.788	0.961	0.956	1
	0.895	0.111	0.896	0.895	0.895	0.788	0.961	0.961	Wt Avg.
Logit Boost	0.770	0.406	0.700	0.770	0.733	0.371	0.753	0.773	0
	0.594	0.230	0.678	0.594	0.633	0.371	0.753	0.704	1
	0.691	0.327	0.690	0.691	0.688	0.371	0.753	0.742	Wt Avg.
Stacking	1.000	1.000	0.551	1.000	0.711	?	0.500	0.551	0
	0.000	0.000	?	0.000	?	?	0.500	0.449	1
	0.551	0.551	?	0.551	?	?	0.500	0.505	Wt Avg.
Decision Table	0.836	0.397	0.721	0.836	0.774	0.454	0.811	0.831	0
	0.603	0.164	0.749	0.603	0.668	0.454	0.811	0.786	1
	0.731	0.293	0.734	0.731	0.726	0.454	0.811	0.811	Wt Avg.
J48	0.862	0.176	0.857	0.862	0.860	0.686	0.858	0.842	0
	0.824	0.138	0.829	0.824	0.827	0.686	0.858	0.794	1
	0.845	0.159	0.845	0.845	0.845	0.686	0.858	0.820	Wt Avg.
Random Forest	0.960	0.094	0.926	0.960	0.943	0.870	0.985	0.987	0
	0.906	0.040	0.949	0.906	0.927	0.870	0.985	0.982	1
	0.936	0.070	0.936	0.936	0.935	0.870	0.985	0.985	Wt Avg.
Random Tree	0.856	0.184	0.851	0.856	0.854	0.673	0.836	0.808	0
	0.816	0.144	0.822	0.816	0.819	0.673	0.836	0.753	1
	0.838	0.166	0.838	0.838	0.838	0.673	0.836	0.784	Wt Avg.
Voted Perceptron	0.673	0.554	0.599	0.673	0.634	0.122	0.560	0.584	0
	0.446	0.327	0.526	0.446	0.483	0.122	0.567	0.489	1
	0.571	0.452	0.566	0.571	0.566	0.122	0.563	0.541	Wt Avg.
Multilayer Perceptron	0.696	0.633	0.574	0.696	0.629	0.066	0.557	0.610	0
	0.367	0.304	0.495	0.367	0.421	0.066	0.557	0.501	1
	0.548	0.486	0.539	0.548	0.536	0.066	0.557	0.561	Wt Avg.

Class (eye-state): 0: Open State; 1: Closed State; TP Rate: True Positive Rate ; FP Rate: False Positive Rate; Precision: (Table 1); Recall: (Table 1); F-Measure: (Table 1); MCC: Matthews Correlation Coefficient ; ROC Area: Receiver Operating Characteristics ; PRC Area: Precision Recall Curve.

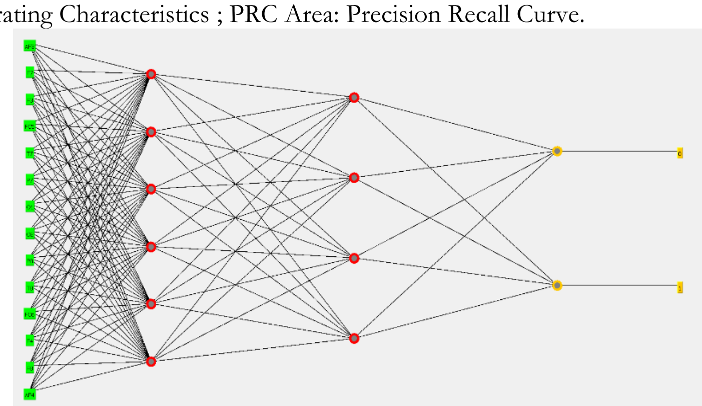

Figure 2. Structure of MLP architecture using the dataset attributes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 and Eye detection) in two hidden layers. The feed-forward neural network connecting all the neurons is shown.

Table 3. The EEG eye dataset from UCI machine learning repository was classified using WEKA software tool and the resultant statistics were shown.

Classifiers	Time, s	Correct Classifier (%)	Incorrect Classifier (%)	Kappa	MAE	RMSE	RAE (%)	RRSE (%)
Naïve Bayes	0.08	46.36	53.64	0.0007	0.5346	0.6969	108.05	140.11
SMO	0.69	55.13	44.87	0.0002	0.4487	0.6699	90.70	134.68
Bagging	1	89.53	10.47	0.7874	0.2116	0.2904	42.76	58.39
Logit Boost	0.32	69.13	30.87	0.3687	0.4115	0.4479	83.18	90.06
Stacking	0.06	55.12	44.88	0	0.4948	0.4974	100	100
Decision Table	1.37	73.10	26.90	0.4463	0.3562	0.4184	72.00	84.12
J48	0.67	84.48	15.52	0.6861	0.1692	0.378	34.20	75.99
Random Forest	4.08	93.56	6.43	0.8694	0.1896	0.2533	38.32	50.92
RandomTree	0.08	83.83	16.17	0.6729	0.1617	0.4022	32.69	80.86
Voted Perceptron	1.05	57.12	42.88	0.1209	0.4288	0.6548	86.68	131.65
Multilayer Perceptron	9.29	54.81	45.19	0.064	0.4864	0.4977	98.31	100.07

Total Number of Instances: 14980; MAE: Mean absolute error; RMSE: Root mean squared error; RAE: Relative absolute error; RRSE: Root relative squared error.

Table 4. Performance evaluation of each chosen classifier

Classifiers	Precision (%)	Recall (%)	F-Measure (%)	Accuracy (%)
Navie Bayes	55	14	22	46
SMO	55	100	71	55
Bagging	89	92	90	89
Logit Boost	70	77	72	69
Stacking	55	100	71	55
Decision Table	72	83	77	73
J48	85	86	86	84
Random Forest	92	96	94	93
Random Tree	85	85	85	83
Voted Perceptron	59	67	63	57
Multilayer Perceptron	57	69	62	54

True positive rate values were shown in Table 5. They were obtained for the classifiers in the following order: Random Forest > Bagging > J48 > Random Tree > Decision Table > Logit Boost > Voted Perceptron > SMO > Stacking > Multilayer Perceptron > Naïve Bayes.

Out of the 11 classifiers used in the evaluation of the EEG Eye-state dataset, Random Forest yielded highest Precision, Recall, F-Measure and Accuracy. Followed by J48, Random Tree performed well. The least performance evaluation was obtained for the classifiers such as Naïve Bayes and SMO. Furthermore, the 'experimenter' environment in WEKA enables to compare the performance of classifiers and hence the top five best performed classifiers namely Random Forest, Bagging, Random Tree, J48 and Decision Table were compared to evaluate their statistical performance. Random Forest and Bagging yielded the significant value ('v') (Figure 3). Hence, it is recommended as per the results obtained in the present study to use Random Forest classifier to predict the accuracy of the EEG Eye state dataset.

Table 5. Confusion matrix for the correctly and incorrectly classified instances of EEG Eye dataset for each chosen classifier in WEKA software tool

Parameters		a	b	McNemar Test* Measures of the association at 1 d.f. and 2-tail	
				Value	**P- value**
Naïve Bayes	a	1162	7095	4713	<0.0000001
	b	941	5782		
SMO	a	8257	0	6721	<0.0000001
	b	6722	1		
Bagging	a	7633	624	65.67	<0.0000001
	b	945	5778		
Logit Boost	a	6360	1897	149.3	<0.0000001
	b	2728	3995		
Stacking	a	8257	0	6722	<0.0000001
	b	6723	0		
Decision table	a	6899	1358	427.9	<0.0000001
	b	2671	4052		
J48	a	7115	1142	0.723	0.3952**
	b	1183	5540		
Random Forest	a	7928	329	97.13	<0.0000001
	b	635	6088		
Random Tree	a	7068	1189	0.8357	0.3606**
	b	1234	5489		
Voted Perceptron	a	5559	2698	164.2	<0.0000001
	b	3725	2998		
Multilayer Perceptron	a	5744	2513	449.3	<0.0000001
	b	4257	2466		

a=Positive; b=Negative. The P-values shown are at 95% confidence interval indicating the significant difference between the false negatives and false positive except for the two classifiers**

Figure 3. WEKA Experimenter environment showing the comparison of the five chosen classifiers one from each folder used in the present investigation. Random Forest (RF) and Bagging yielded significant values ('v'), Random Tree and Decision Table gave in-significant value ("*") with a poor response. On the other hand, J48 classifier was found to be relatively moderate and nearer to RF and Bagging.

The prediction of either the class '0' or '1' for the edited EEG eye state test dataset using Random Forest yielded the accuracy in the ratio of 7:3 (correct:incorrect) and attained 93.5% accuracy (Figure 4).

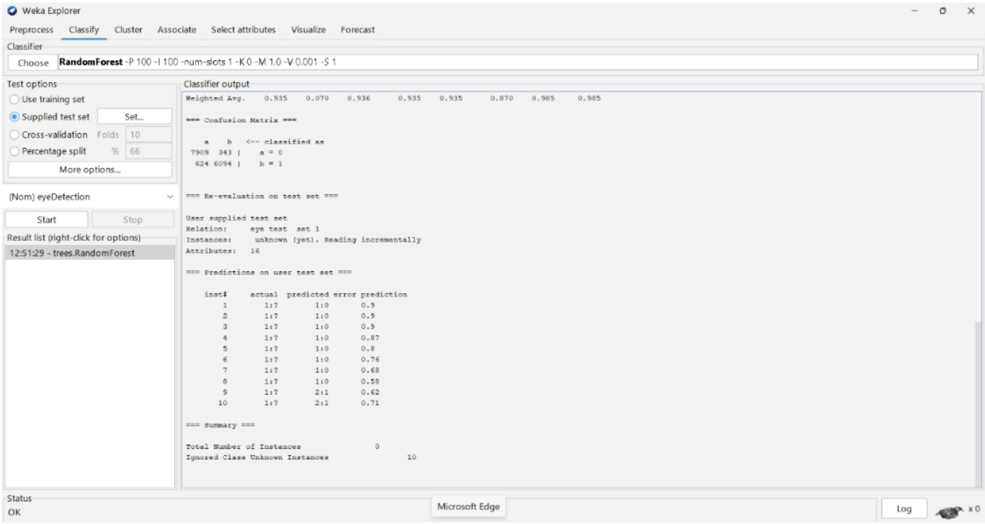

Figure 4. The prediction of the class '0' or '1' for the edited EEG Eye-state dataset using Random Forest yielded the accuracy in the ratio of 7:3 (correct: incorrect) and attained 93.5% accuracy.

Discussion

The performance evaluation of the classifiers applied on EEG eye-state dataset as given in the Table 4 revealed that the following five classifiers shown as the best in the order Random Forest>Bagging>Random Tree>J48>Decision Table and accordingly their derived percent specificity values are 94.8, 90.2, 82.0, 82.9 and 74.8 respectively. These observations reflect that the Radom Forest classifier algorithm is the best suited for the EEG eye-state dataset, which was also authenticated by the Experimenter environment in WEKA tool (Figure 3). The analyzed test dataset comprising 10 instances chosen randomly from the UCI Machine Learning Repository yielded the ratio as shown in Figure 4.

Machine learning approach for early diabetic prediction was proposed by Haq et al. [15]. Deepika et al. [16] worked on the prediction of chronic kidney disease on the dataset containing 24 attributes and 1 target variable. Deepika et al. [16] used the KNN and Naive Bayes supervised machine learning algorithms to develop the model. KNN and Naive Bayes both obtained accuracy levels of 91% and 97% respectively. Al-Taie et al. [17] developed an effective approach using Multilayer Perceptron (MLP) for detecting cardiac disease as an application of data mining and accuracy at 74.85%. Radpour and Gharehchopogh [18] conducted a study where scientists used the clinical records of heart disease of 40 individuals. The criteria employed by them for identification included age, gender, blood pressure, and tobacco usage. 85% cases were properly predicted by their model Multilayer Perceptron (MLP) classifier in WEKA software tool. In a real-time system, it was possible to predict eye-states using EEG records with an accuracy ranging from about 96% to over 99% according to Piatek et al. [14]. ANN was regarded as the most accurate forecast of the user's eye condition according to Hassan et al., [19]. The Naive Bayes classifier has the highest accuracy as reported by Al-Taie et al. [17]. In another study, it is shown that Random Forest and Instance Based Classifiers like IB1 and IBK performed better according to Mridu Sahu et al. [20].

The individual human being attitude with others, the response in problem solving situation, the consolidation of thought processes, the cheerful reciprocation, and many other behavioral reflexes follow a set pattern of brain-waves (Figure 1) as there is a continuous propagation of impulses in the brain. In the neurological disorders which normally arise either due to ageing or illness, the identification of the pattern of brain waves will assess the state of the health of a person. It was shown that the 'eye-opened' gives distortion in wave patterns and 'eye-closed' presumably yields the undisturbed brain-wave patterns in EEG recordings. Hence, in the present study, the EEG eye-signal test dataset with 15 attributes (brain-wave determining markers using plugged electrodes) were evaluated using the classifiers in WEKA tool. The best classifier namely Random Forest predicted the edited test dataset in the ratio of 7:3 (correct:incorrect).

List of abbreviations (if any)

ARFF: Attribute Related File Format
EEG: Electroencephalograph
J48: Algorithm to generate decision tree
MLP: Multilayer Perceptron
SMO: Sequential Minimal Optimization
UCIMLR: University of California Irvine Machine Learning Repository
WEKA: Waikato Environment for Knowledge Analysis

Conflict of Interest

The authors declare that they have no conflict of interest.

Authors' Contributions (not compulsory)

Srivalli Polisetty explored the WEKA tool, performed the experiment with WEKA using classifiers, and wrote the Introduction and methodology sections. Krupanidhi Sreerama chose the topic, guided in exploring WEKA tool, and writing the methodology, results, and discussion sections. Both authors revised the manuscript.

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