Ensemble Learning Based on Soft Voting for Detecting Methamphetamine in Urine

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***Abstract*— Recently, as the rapid progress of information and communication technology, robot technology, and artificial intelligence, we have become to build a higher level of safe, comfortable, and smart society coexisting with advanced technology. Methamphetamine addiction has become a major human social problem in the world. Traditional approaches of detecting methamphetamine through hair, skin, urine, and blood fluid are financially inefficient, time-consuming, and in some cases too complicated. Providing reliable and trustworthy detection with the highest precision and accuracy is of a challenging task. This paper proposes ensemble learning using a soft voting approach to improve the accuracy of detection. First, we trained five individual classifiers, namely adaptive neuro-fuzzy inference system (ANFIS), random forest, multi-layer perceptron (MLP), k-nearest neighbor (k-NN), and support vector machine (SVM) on the same urine dataset. We then created new ensemble learning using the soft voting approach by averaging the probability of individual ANFIS, random forest, MLP, k-NN, and SVM. Firefly algorithm for weight optimization is used to strengthen individual classifiers to form an ensemble and increase the prediction accuracy. Our proposed ensemble produces 100% in both accuracy value and F1-score value compared to the individual classifiers mentioned above.**

Keywords— methamphetamine detection, ensemble classifier, soft voting, firefly algorithm.

I. INTRODUCTION

Recently, as the rapid progress of information and communication technology, agent technology, robot technology, and artificial intelligence, we have become to build a higher level of safe, comfortable and smart society coexisting with advanced technology. Such a society should be discussed from the viewpoint of Human Symbiotic Systems, and we have to consider and design intelligent interaction with the bidirectional communication the coexisting and symbiosis between the human and the artifact such as intelligent agents and robots. Furthermore, we have to consider the relationship among people in such a society facing to cyber terrorism, environmental threats, and influenza pandemic. For example, there are many problems such as the use of drugs or methamphetamine in human society.

Methamphetamine is a stimulant that increases monoamine levels in the centralized nervous system, which is considered to be benefit to treat obesity and alcohol dependency patients [1]. On the other hand, it has many harmful negative side effects, such as produces euphoria, mood, and energetic feelings [2] and increases blood pressure, heartbeat, and body temperature equilibrium [3]. A major destructive effect of methamphetamine is an addiction, which could cause many problems for human society [4, 5]. Detecting methamphetamine in urine is a challenging task. Various methods for measuring methamphetamine have been proposed in different biological samples including hair, skin, urine, and blood fluid [6]. Nonetheless, since most of these approaches are financially inefficient, time-consuming, and in some cases too complicated, they are not suitable [7].

Providing reliable and trustworthy detection method with the highest precision and accuracy and lowest error rates is challenging task and very important issue due to its close relationship to individual life. If the urine screen test to a human is positive for methamphetamine, this will have a serious impact on the human.

Anomaly detection has always been the research direction of many fields, and many related detection methods and systems have been developed until now. Detecting the anomaly of urine containing methamphetamine precisely becomes a challenge task. Traditional detection tools of methamphetamine using multi-drug rapid test, are commonly used in forensic. We need to design a smarter detection tool. This anomaly detection tool requires the capability to learn dynamically and requires environmental adaptation to produce more accurate real time detection.

Various types of learning approaches have been applied to classification problems, and the learning capability has been drastically improved nowadays. Furthermore, a study on explainable artificial intelligence has also become popular to discuss the interpretability of trained model. However, we often need the reason of classification results to satisfy the accountability and responsibility. One of the main tasks of machine learning is to build a good model from a given dataset. Strong classifiers are desirable but are difficult to find.

Each classification method has its own different feature used in the classification task, e.g., nonlinearity and similarity. Therefore, after obtaining the classification results from multiple classification methods, we can analyze the reason of the classification. The concept of aggregating several classifiers into a single final classification.is known as the ensemble approach [8]. Accordingly, in this paper, we try to use many different types of classification methods in the framework of ensemble learning.

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The idea of combining many classifiers has taken advantage of anomaly detection and many more issues in classification in recent decades. Ensemble-based classifiers are well-studied and have been used to improve the accuracy of several classification tasks by combining multiple models, which is better than a single model. An ensemble generated from classifiers trained from the same learning algorithm is termed homogeneous, whereas one generated from classifiers trained from different learning algorithms is a heterogeneous ensemble. The success of the ensemble classifier is strongly dependent on the diversity of the outputs of its classifiers and how these outputs can be combined into a single one [9]. Usually, the generalization capability of the ensemble is better than that of a single classifier, as it can boost weak classifiers to produce better results than can a single strong classifier.

The ensemble learning model is superior to the single model in both predictive power and generalization capability. Accordingly, in this paper, we utilize many different types of classification methods in the framework of ensemble learning to improve the detection quality. To the best of our knowledge, this is the first ever approach to detect methamphetamine using an ensemble learning approach. We trained five classifiers, namely adaptive neuro fuzzy inference system (ANFIS), random forest, multi-layer perceptron (MLP), k-nearest neighbor (k-NN), support vector machine (SVM) on the same urine dataset. We then created a new ensemble learning approach using soft voting approach. An optimal weight probability using firefly algorithm (FA) is used to strengthen individual classifiers to form an ensemble and increase the prediction accuracy. FA performs better in many optimization problems [10-12].

The rest of the paper is organized as follows. Section 2 presents the related work. We present our data collection and system model in Section 3. We conduct experiments and evaluate the performance, continued with discussion some of the details of our models and experimental methods in Section 4. Finally, we conclude our work in Section 5.

II. Related Works

The detection of methamphetamine has been developed using many methods. A rapid quantitative measurement using an electro-microchip has been successfully developed by C.H. Yeh et al [13] to detect the impedance signals of various methamphetamine concentrations based on the developed competitive immunoassay method. A new digital signal processing approach has been introduced since 1997 [14] based on asymmetric adaptive curve adjustment and its output was measured using real field test data obtained using different methamphetamine and nicotine mixtures in the spectrometer. A predictive face age model presenting the horrifying effects of drugs specially methamphetamine addiction on an individual appearance age has been conducted using statistical survey method [15].

Many applications of classifier and ensemble technique have been widely used for detection. ANFIS was used to construct a robust ensemble learning for medical volume analysis [16]. ANFIS with bagging was used to create an accurate ensemble of fuzzy classifiers for classifying twenty data sets [17]. A random forest-based ensemble based on different sensor feature sets was proposed for human activity recognition to build a more stable, more accurate and faster classifier [18]. Random forest ensemble classifier improves classification of arrhythmia disease and increases the classification accuracy by 1.38 (%), 7.05 (%) and 2.66 (%), respectively, for thyroid, cardiotocography, and audiology datasets [19].

A multilayer perceptron (MLP) ensemble with pre-processing time series transformations and post-processing long term seasonality adjustments was proposed to enhance forecasting performance [20]. The MLP Ensembles appeared a promising tool for developing SDMs that would produce a precise small-size [21], freshwater fish models and for e-flow evaluations [22]. A new ensemble learning method constructed from individual SVM and k-NN was proposed to improve the robustness in detecting traffic incidents [23]. A novel ensemble method constructed from k-NN and SVM that uses PSO generated weights has been proposed to create ensemble of classifiers with better accuracy for intrusion detection [24].

As far as we know, the application of ensemble technique has not yet been used for methamphetamine detection. The contribution of this paper is to improve the detection of methamphetamine using a new ensemble technique constructed from individual ANFIS, random forest, MLP, k-NN, and SVM.

III. Method

This section describes data collection, system design, individual classifiers: ANFIS, random forest, MLP, k-NN, and SVM; and proposed ensemble learning approach.

A. Data Collection

Data collection is carried out to obtain reliable participant information. We designed a hardware to collect data, which is comprised of three circuits, namely electronic nose circuit, heating circuit and blower circuit, as shown in Fig. 1. Electronic nose consists of 1 Arduino equipped with 4 gas sensors, namely the hydrogen susceptible MQ-2 and MQ-8, the nitrogen sensitive MQ-131 and the MQ-135 sensors, as shown in Fig. 2. Each VCC pin on each gas sensor transmits a 5V pin on Arduino and the GND pin on Arduino allows access to each GND on each gas sensor. The analog pin in A0, A1, A2, A3 on the Arduino is linked with the AO pin on MQ 8, MQ 135, MQ 2, MQ 131, respectively. The hardware design heating circuit consists of a heater that can be connected directly to 220V AC voltage while the blower circuit is composed of an 12V power supply and a 12V DC fan. We obtained 700 samples of urine from the Semarang Police Academy Forensic Laboratory, Semarang, Indonesia, and 350 samples had positive methamphetamine, and 350 had negative methamphetamine. This urine produces aromas that will be detected by the electronic nose.

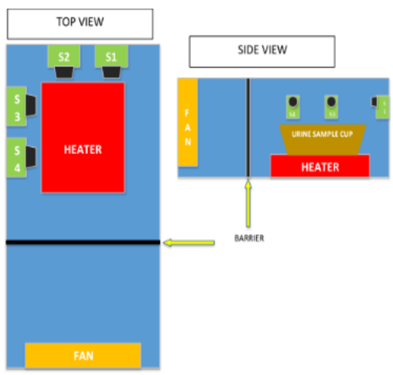

Fig. 1. Hardware circuit to collect data

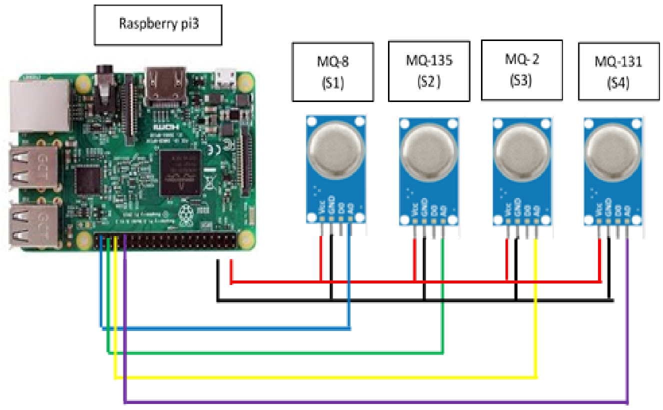

Fig. 2. Four gas sensors connected to raspberry pi3 to extract urine

B. System Design

Determining the anomaly of urine containing methamphetamine precisely becomes a challenge task. Five individual classifiers, namely ANFIS, random forest, MLP, k-NN, SVM are used to construct new ensemble learning. Fig. 3 shows the system design architecture of ensemble learning of five classifiers. First, we train individual classification models: ANFIS, random Forest, MLP, k-NN, and SVM. We employed firefly algorithm to determine the optimum weight to improve prediction accuracy. The test set is then assigned respectively to ANFIS, random forest, MLP, k-NN, and SVM models and the outputs of the five models will be incorporated into the ensemble model using soft voting method to produce the final output by averaging their individual probability.

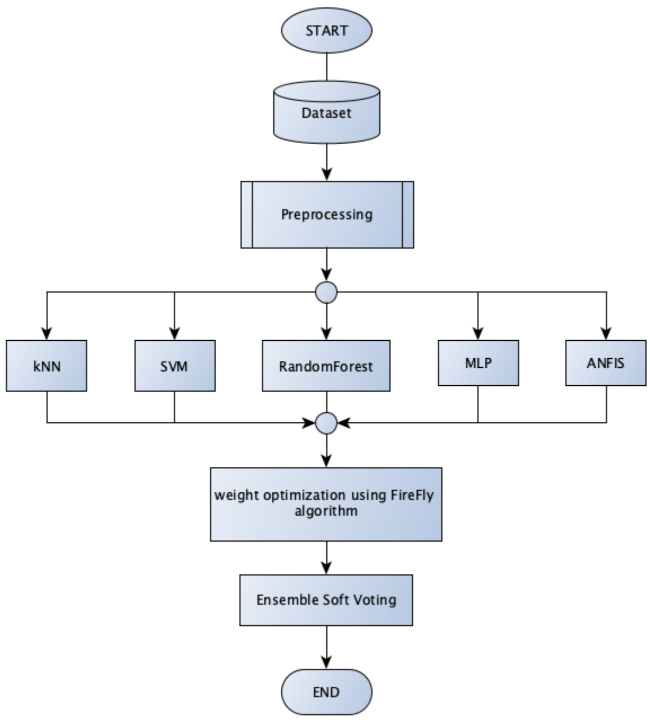

Fig. 3. System design of ensemble learning of five classifiers

C. ANFIS

Adaptive-Network-based Fuzzy Inference System (ANFIS) was introduced by Jang [25], as a basis to construct a set of fuzzy if-then rules with appropriate membership functions implemented under adaptive network structure. Adaptive network as shown in Fig. 4, is a superset of feedforward neural consisting of nodes and directional links connected to nodes [25]. Furthermore, some or all nodes are adaptive, meaning that their outputs depend on parameters relevant to these nodes, and the learning rule defines how these parameters are to be changed to minimize a specified error measure. The adaptive capabilities in an adaptive network structure are shown using square and circle nodes. A square node denotes an adaptive node with parameters whereas a circle node denotes a fixed node with no parameters. The links in an adaptive network are not correlated with any weights, they only reflect the direction of signal flow between the nodes.

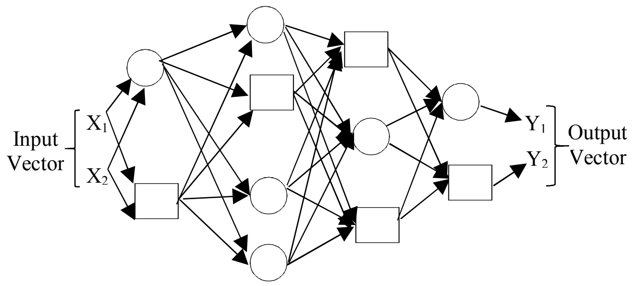

Fig. 4. Adaptive network structure [25]

D. Random Forest

Random Forest (RF) was chosen for this ensemble method as the basic algorithm. RF developed by Breiman [26] is an ensemble learning algorithm for classification, regression and other tasks, generated by random samples to build each tree in the forest, as shown in Fig. 5. A random forests classifier consists of collection of decision tree classifiers defined as $\{h(x, \varpi_k), k=1,...\}$. Here, ϖ_k represents identically distributed random vectors and each tree casts a unit vote for the most popular class at input x.

The following steps are to build a decision tree in the forest [19]:

1. The number of trees (T) to be grown is chosen.
2. The number of features (f) to split each node is chosen. If the feature set of the input data is denoted by F, then foF must be satisfied. The subset of features f is kept constant during the formation of forest.
3. T number of trees is grown with the following criteria:
   a) A bootstrap sample of size n is constructed and a sample of Sn is selected to grow a tree.
   b) To grow a tree at each node, m features are selected randomly and they are used to find the best split.
   c) The tree is grown to the maximal extent with no pruning.
4. To classify a sample X, a majority voting scheme is used to evaluate votes from every tree in the forest.

The performance of random forest depends on the variety of forest trees. This is achieved by randomly selecting functions at each tree node and then using the highest-level learning attribute. One of the effective properties of an algorithm for random forests is that it is not overfit, even if more trees are added to the forest.

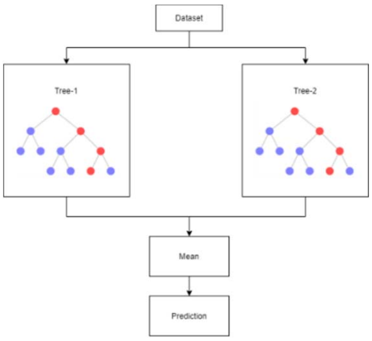

Fig. 5. Random forest

E. Multi Layer Perceptron (MLP)

Artificial Neural Network (ANN) or known as a neural network, is a well-known machine learning approach for dealing with the dynamic, time-serial, and classified problem patterns in data types [27]. The nonparametric version of neural networks basically allows the methods to be established without prior information or knowledge of the data population distribution or the possible interaction effects between different variables. Even though there are several types of ANNs, this study uses only multi-layer perceptron (MLP) network.

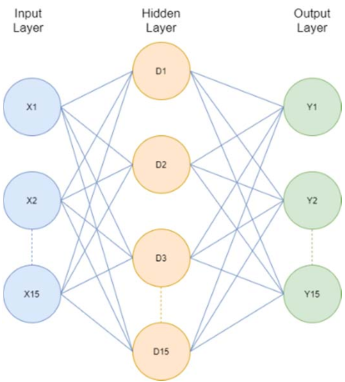

Fig. 6. Multi-layer perceptron network

MLP is a type of artificial neural network feedforward model which uses backpropagation for the training network [28]. MLP consists of multiple node layer (input and output layer with one or more hidden layers) in a graph that maps input data to suitable outputs, as shown in Fig. 6. In this study, an MLP neural network with two hidden layers, an input layer with 9 neurons and an output layer with 2 neurons, was used.

F. k-Nearest Neighbor (k-NN)

k-Nearest Neighbor (k-NN) is a simple and effective method used to solve classification, estimation and prediction problems that require unlabeled object distance calculation for all objects marked in the training set [29]. Due to its simplicity and versatility, the training process of k-NN is very fast. The entire training dataset is the k-NN representation model itself. The k-NN prediction is analyzed by searching the entire training dataset for the most related K neighbors directly and summarizing the prediction for those K neighbors as shown in Fig. 7. To identify nearest neighbors, the k-NN uses the distance metric, such as: (1) Hamming Distance, which calculates the distance between binary vectors; (2) Manhattan Distance, which calculates the distance between real vectors using the sum of their absolute difference; (3) Minkowski Distance, which is generalization of Euclidean and Manhattan distance. In the classification process, it is the class mode labels that classify each unlabeled in training set from the K-most similar (neighbor) instances.

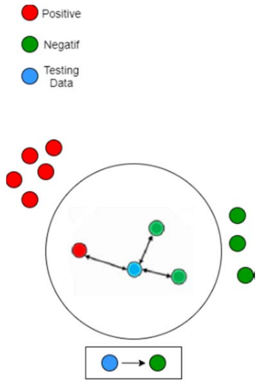

Fig. 7. k-Nearest Neighbor

G. Support Vector Machine (SVM)

Cortes and Vapnik propose SVM [30], which is used widely in problems of classification and regression. SVM is a kernel learning method, which uses the training set to construct a hyperplane for classifying the test samples, the function of the hyperplane can be described as: f (x) = ωx + b where f (x) is a hyperplane function. ω is a normal vector of the hyperplane and b is a variable.

Suppose the training set can be described as:

$S = \{(x_1, y_1), (x_2, y_2), ..., (x_h, x_h), \dots, (x_l, y_l)\}$

where x_h denotes any one training sample, and $x_h \in R$ n , h = 1, 2, . . . , l. $y_h \in \{-1, 1\}$ is the class label for x_h. l is the number of the training sample. SVM model as shown in Fig. 8.

The principle idea of SVM is to search for an optimal hyperplane meets the classification requirements and uses a certain algorithm to maximize the margin of separation next to the optimal hyperplane, while ensuring correct classification.

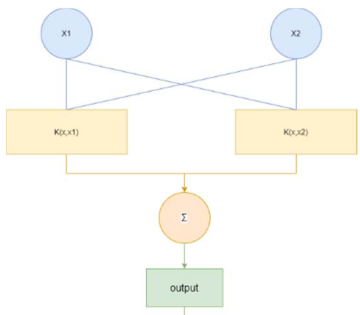

Fig. 8. SVM.

H. Firefly Algorithm (FA)

Biologically based optimization approaches have been widely used in numerous optimization problems [31, 32] because of their simplicity, robustness, and ability to effectively address complex optimization issues. The metaheuristic algorithms are considered the most suited to global optimization amongst these biology-derived algorithms because metaheuristic uses certain randomizations and local searches as randomization provides a good way from local search to global searching [33].

Firefly Algorithm (FA) is a metaheuristic developed by Xin-She Yang for the first time at Cambridge University in late 2007 and 2008, inspired by flashing behavior of fireflies [34-36]. FA has three rules to idealize the behavior patterns of fireflies [35]:

a. All fireflies are unisex. Each firefly can be attracted to other fireflies regardless of their sex.
b. A firefly 's attractiveness is determined by its brightness. The less bright firefly tends to fly towards the brighter one. The brightness and the attractiveness decrease as the distance increases. The brightest firefly flies at random.
c. The brightness of a firefly is dependent on the landscape of the objective function.

This study used FA for weight optimization of each individual classifier to construct the ensemble classifier.

I. Proposed Ensemble using Soft Voting method

The concept behind the ensemble learning method is to boost the performance of a predictive model by combining the predictions of several classifiers. Voting is the easiest way to incorporate prediction from several classifiers by using a majority vote (hard vote) or the average predicted probabilities (soft vote) to predict the class labels. This study employs a soft voting method by adding the weight optimization parameter to individual classifiers (ANFIS, random forest, MLP, k-NN, and SVM) using FA algorithm. When optimum weight obtained from FA is assigned, the probabilities are collected, multiplied by the classifier weight, and averaged. The final class label is then obtained from the class label with the highest average probability.

IV. Results and Discussion

We implemented the algorithm in Matlab R2019a. To enhance the credibility of the experiment, the training set (90% of the dataset) and the testing set (10% of the dataset) were selected randomly ten times from a total of 700 data under the same conditions. Therefore, there were ten sets of training and test data in the experiment, and the final result was based on each set of the data's result. We summarize the performance of ensemble classifier using accuracy and F1-score.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$F1\ score = \frac{2TP}{2TP+FP+FN} \quad (2)$$

Accuracy refers to a classifier being correctly categorized in a two-class issue, i.e., normal or abnormal. the F1- score is used to evaluate the results of the detection. The five ensemble methods as shown in Table 1 are compared by two different elements: (1) the average accuracy value and the accuracy variance value; and (2) the mean F1 score measurement value and the F1 score measurement variance value. The average value represents the overall performance and the average reflects the degree of stability.

TABLE I. Experimental Results of Individual Classifiers and Proposed Ensemble Classifier

Classifier	Weight	Average Accuracy	Average F1-score
ANFIS	0.4015	95.45%	95.45%
Random Forest	0.8224	99.35%	99.35%
MLP	0.7696	99.35%	99.35%
k-NN	0.4466	96.75%	96.75%
SVM	0.4500	94.16%	94.16%
Proposed Ensemble Classifier		**100%**	**100%**

Table 1 shows that the proposed ensemble classifier has the highest accuracy value and F1-score value among five individual classifiers. Therefore, the performance of the proposed ensemble classifier is the best among five classifiers mentioned above. We applied the proposed ensemble for detecting positive and negative methamphetamine in urine as shown in Fig. 9 and Fig. 10, respectively.

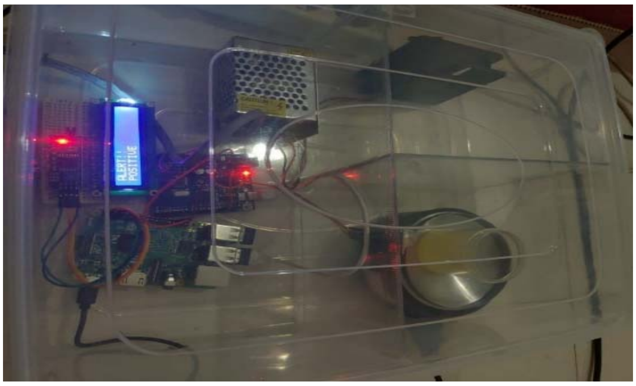

Fig. 9. Positive alert of methamphetamine using proposed ensemble

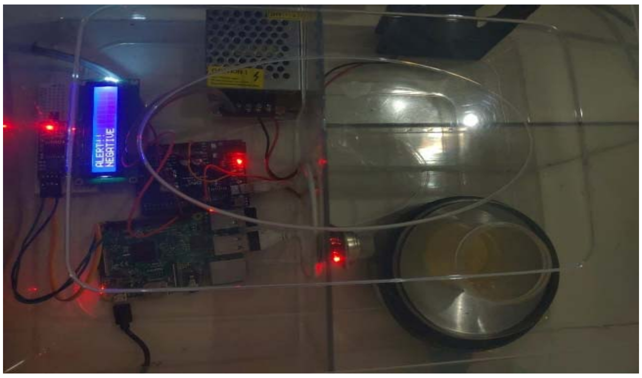

Fig. 10. Negative alert of methamphetamine using proposed ensemble

V. Conclusion

This paper proposes a new ensemble classifier in methamphetamine in urine detection, which accepts the results of soft clustering. It employs the individual ANFIS, random Forest, MLP, k-NN, and SVM models firstly, and then it takes one ensemble learning strategy to combine them for better final output by averaging individual probability. This study uses the firefly algorithm for weight optimization. The experimental results show that the proposed ensemble classifier has achieved the best performance of 100% among all the compared methods. More importantly, the ensemble learning strategy has also improved the robustness of the individual models. There is no excuse not to incorporate ensemble learning strategies in a learning situation that ensembles learning is ideal for. As future work, we intend to develop an ensemble learning method to improve the interpretability of trained models. We will also attempt to research soft clustering algorithms and use them to generate dependent clustering results with diversity.

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