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Detection of Counterfeit Banknotes Using Genetic Fuzzy System

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Abstract

Due to developments in printing technology, the number of counterfeit banknotes is increasing every year. Finding an effective method to detect counterfeit banknotes is an important task in business. Finding a reliable method to detect counterfeit banknotes is a crucial challenge in the world of economic transactions. Due to technological development, counterfeit banknotes may pass through the counterfeit banknote detection system based on physical and chemical properties undetected. In this study, an intelligent counterfeit banknote detection system based on a Genetic Fuzzy System (GFS) is proposed to detect counterfeit banknotes efficiently. GFS is a hybrid system that uses a network architecture to fine-tune the membership functions of a fuzzy inference system. The learning algorithms Fuzzy Classification, Genetic Fuzzy Classification, ANFIS Classification, and Genetic ANFIS Classification were applied to the dataset in the UCI machine learning repository to detect the authenticity of banknotes. The developed model was evaluated based on Accuracy (ACC), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Error Mean, Error STD, and confusion matrix. The experimental results and statistical analysis showed that the classification performance of the proposed model was evaluated as follows: Fuzzy = 97.64%, GA_Fuzzy = 98.60%, ANFIS = 80.83%, GA_ANFIS = 97.72% accuracy (ACC). This shows the significant potential of the proposed GFS models for fraud detection.

Keywords: ANFIS, Counterfeit banknotes, Fuzzy inference system, Genetic fuzzy system, Genetic algorithm.

1 | Introduction

Paper money remains a common means of exchanging goods and services. With advances in digital imaging technology, color scanners, and laser printers, it is becoming easier to create high-resolution counterfeit banknotes. Counterfeit banknotes are becoming more common because they look very similar to real money and are difficult for the untrained eye to detect. Companies and organizations are losing money due to the widespread use of counterfeit banknotes. Therefore, it is important to develop an effective technique for detecting counterfeit banknotes. Counterfeit detection devices [1] exist, but they are sometimes prohibitively expensive, making counterfeit detection a major concern for financial and government institutions with little community involvement.

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The process of certifying banknotes also continues to improve as new strategies for producing counterfeit money are invented every day. The elimination of transaction problems is inextricably linked to the successful detection of counterfeit banknotes. Serious measures are needed to protect the economy from such immoral acts. Artificial intelligence approaches based on Machine Learning (ML) have recently become the de facto standard for banknote categorization difficulties [2]-[4]. The goal of ML must be to complement human decision making, but some approaches are superior at doing so. For applications that require explanation and are prone to unforeseen and unpredictable failures, ML techniques should be preferred over traditional approaches.

There are approaches to this problem based on both the latest technology and traditional computer vision methods, as well as alternative solutions. Nearest Neighbor Interpolation [5]-[7], evolutionary algorithms [8]-[10], and fuzzy systems [11]-[13] are examples of techniques that can be used. Due to its high accuracy and generalization capability for new data, it can beat both standard ML approaches and humans in classification tasks, which is compatible with learning-based methods. Various options were presented to detect counterfeit banknotes [14]-[16].

Fuzzy Inference System (FIS) is an intelligent system capable of explaining difficult facts [17]-[20]. Fuzzy systems are architectures capable of understanding language norms in decision scenarios and effectively ensuring membership in each category across a wide range of input values. The FIS parameters used in this work were optimized using the Genetic Algorithm (GA) [21]. The term "Genetic Fuzzy System" (GFS) refers to the application of a GA -optimized FIS (GFS) [22]-[27]. When it comes to detecting counterfeit banknotes, a False Positive (FP) is often more damaging than a False Negative (FN), as counterfeit banknotes can lead to greater financial losses if they are not detected.

The remainder of this paper is organized as follows: the materials and methods are described in Secion 2. The data set and the GFS are discussed in this section. Secion 3 presents the experimental results. Finally, Secion 4 contains the conclusion.

2 | Material and Methods

It is difficult to distinguish between counterfeit money and genuine banknotes. It should be possible to automate this process. Because of the accuracy with which counterfeit banknotes are produced, it is necessary to develop an algorithm that can predict whether a particular banknote is genuine or counterfeit. For this purpose, a model was created with the features obtained by analyzing the wavelet variance, wavelet skew, wavelet kurtosis and image entropy of an image sequence derived from real and imaginary banknote-like patterns. Since the variable to be estimated is a binary variable, this is a classification question (fake or legal). In this case, the objective is to simulate the possibility that a banknote is counterfeit while maintaining the functionality of its features.

2.1 | Data Set

The dataset [28] consists of 1372 samples (rows) and 5 variables (columns). Data was collected by digitizing photographs of genuine and counterfeit banknote-like samples using an industrial camera commonly used for inspecting printed products. Features were then extracted from the images using the Wavelet Transformation tool. The following variables are used as inputs to this problem: the Variance of the Wavelet Transformed Image (VWTI), the Skewness of the Wavelet Transformed Image (SWTI), the Kurtosis of the Wavelet Transformed Image (KWTI), and the Entropy of the Image (EI). The target was used as a counterfeit. It can have only two possible values: 0 (no counterfeit) or 1 (counterfeit). The proposed categorization model is shown in *Fig. 1*.

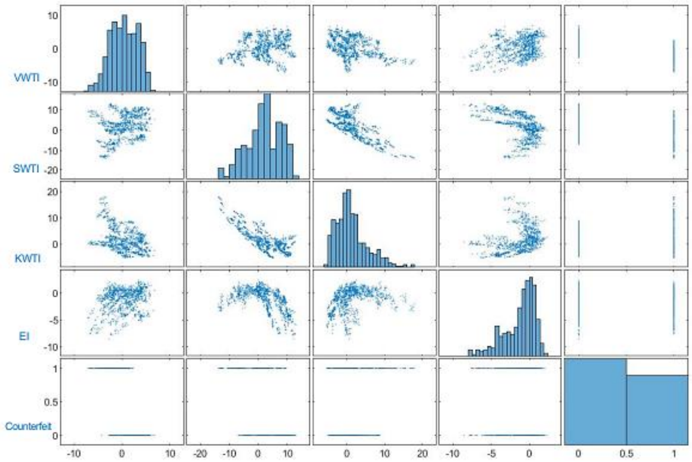

Fig. 1. The scatterplot matrix of the banknote authentication dataset [28].

2.2 | Genetic Algorithm

GA is a technique developed by Holland that is frequently used [29], [30]. To get the best performance from the FIS, its settings need to be adjusted. The procedure is to choose a random solution set for each parameter and update it until an optimal parameter set is reached. This first population is referred to as the "initial population" on GA. By far the most important component of GA is the chromosome. Each chromosome contains genes that serve as parameters for the respective task. To begin solving a problem, an initial population must be created. The responsible member then compares this response to the others based on the survival criteria. Finally, the requirements for optimization completion are set by the number of chromosomes created, and the work is typically done after a certain number of conditions is satisfied [31], [32].

2.2 | Adaptive Neural Fuzzy Inference System (ANFIS)

The FIS is an application of artificial intelligence developed by Jang [33] that mimics human reasoning. It is a simple approach to data learning that uses fuzzy principles (IF THEN) and given inputs and outputs to transform inputs and information links from strongly connected parts of the neural network into desired outputs. ANFIS uses both ANN and fuzzy inference methods to deal with non-linear and complex problems in a unified framework [34], [35]. ANFIS consists of nodes and routed paths, and all input-output values can be changed using the various parameter sets defined when designing the network. ANFIS systems can be used in conjunction with a variety of optimization techniques to minimize errors in the training phase. This goal was also achieved in the scenario used in this study [36]. ANFIS is classified into five levels. They consist of a network of neurons that communicate between the input and hidden layers and the hidden and output layers. Each layer consists of neurons constructed according to the principles of fuzzy control. *Fig. 2* illustrates the structure of the ANFIS algorithm.

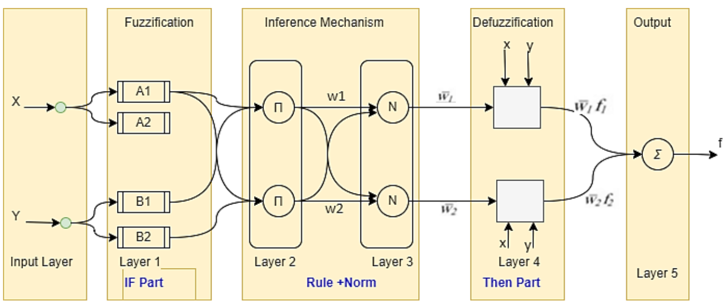

Fig. 2. Structure of ANFIS algorithm [37].

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The proposed GFS model is described with GA-optimized membership function parameters (MFs). These are updated with the release of each GA iteration. Each fuzzy set has a corresponding membership value for each variable, which is in the range [0,1].

2.3 | Genetic Fuzzy System Parameter Optimization

GAs are computer systems based on natural evolutionary processes that use operators that follow the heuristic search process in a search space containing the optimal answer to the optimization question [38]. GA is a stochastic optimization approach based on the principles of genetics and natural selection. GA [39]-[42] is a meta-heuristic optimization approach inspired by natural processes and well suited for optimizing membership function components in FIS [43]-[45]. GA is able to discover extremely large solution spaces due to probabilistic variations. GA is divided into three phases: population generation, GA operators (selection, crossover and mutation) and fitness function evaluation. GA selects participants in several ways, including tournaments and the roulette wheel. Two randomly selected individuals exchange their genes with the crossover operator to produce the next generation. Compared to crossover, the probability of a mutation occurring is low. Since it is easier to construct and debug than the round-based or tournament selection algorithms, a proportional roulette wheel selection algorithm is used in this study instead of the round-based or tournament selection algorithms. It also gives much faster results than the other two methods. One-point crossover algorithms have been developed as part of GA to transfer solution proposals or chromosomes between two different systems. The proposed GFS integrations are very useful in solving complex and nonlinear equations. *Fig. 3* shows the GFS architecture.

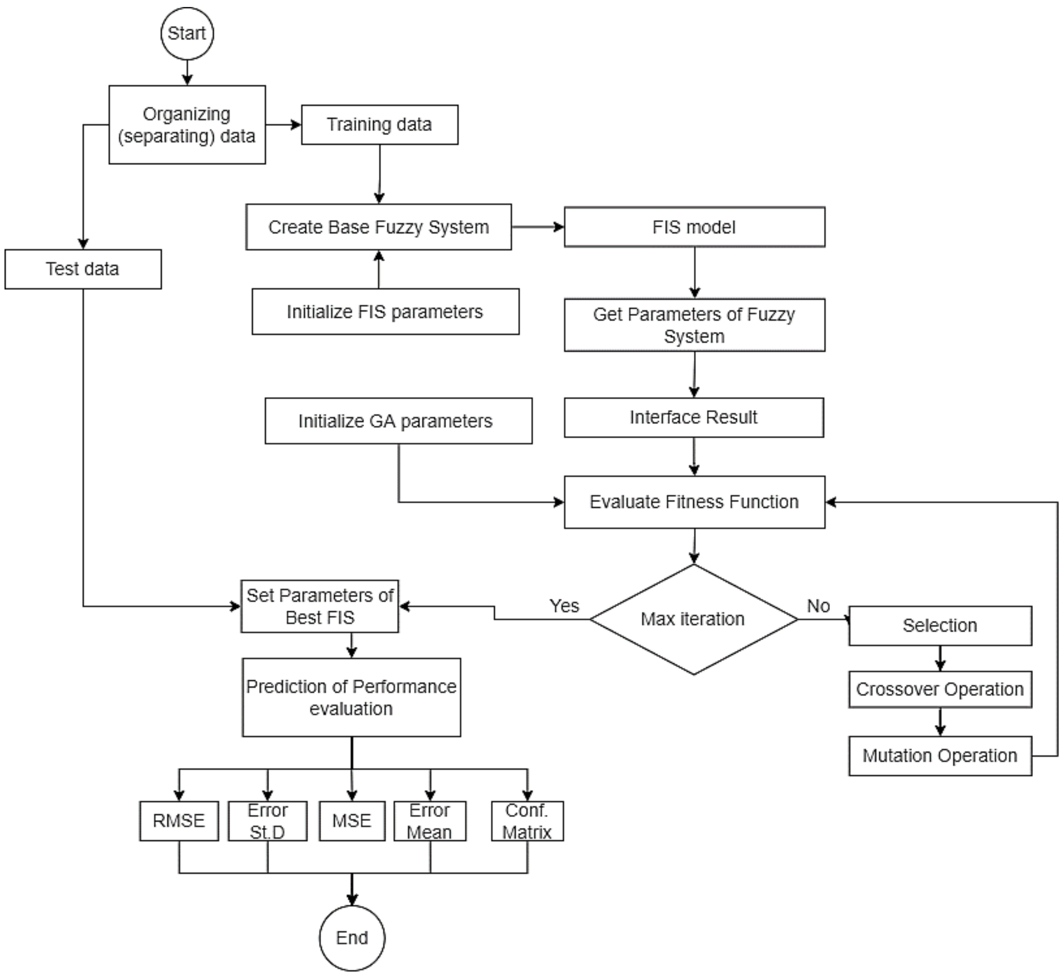

Fig. 3. Flowchart of GFS.

The initial parameters of the algorithm for the proposed model are given below.

Table 1. Initial parameters GFS.

Algorithm	Parameters	Values/types
	Epoch	80
	Error Goal	0
	Input membership shape	Gaussian
ANFIS	Output membership shape	Linear
	FIS generation	FCM
	Step Size Decrease Rate	0.9
	Step Size Increase	1.1
	Initial Step Size	1.1
GA	alpha	1
	VarMin	-(10^alpha)
	VarMax	10^alpha
	MaxIt	25
	nPop	7
	Crossover Percentage	0.7
	Mutation Percentage	0.5
	Mutation Rate	0.1
	gamma	0.2
	Selection Pressure	8
FIS	fcm_U	2
	MaxIter	100
	MinImp	1e-5

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3 | Experiments

In this section, we test and compare the performance of the proposed GFS. The parameters of the FIS structure used here are optimized by a GA. The model to be built uses the decision mechanism to classify the banknotes in question as genuine or counterfeit. As a result, an expert system will increase the quality and efficiency of services while minimizing human error and the need for additional staff. As the following figures show, the technique based on training the FIS with the GA algorithm is more efficient. It has also been shown that the FIS network can be used for a wide range of problems as the GA algorithm has no limitations compared to inference-based techniques and is easy to implement.

3.1 | Evaluation Metrics

MSE, RMSE, error mean, error STD and the confusion matrix were used to assess the performance of the GFS system. Quantitative assessments of the models produced were carried out using a set of performance criteria (*Eqs. (1)-(4)*). The details of each equation can be found in the corresponding reference.

Mean squared error

The mean square error describes the closeness of a regression curve to a given collection of points. The MSE quantifies the performance of an estimator, a ML model. It is always positive, and it can be argued that estimators with an MSE close to zero perform better [46], [47].

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2. \tag{1}$$

Root mean square error

Root Mean Squared Error (RMSE) is a squared metric that evaluates the magnitude of an error in a ML model. It is often used to measure the difference between the expected values of the predictor and the actual values. The RMSE is the standard deviation of the estimation error. An RMSE value of 0 means that the model was error-free [48].

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2}. \tag{2}$$

Error mean

Mean error is the average error between the predicted values of a ML model and the actual values. In this context, the error is the measurement uncertainty or the difference between the estimated value and the actual value [47].

$$\text{Error Mean} = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i). \tag{3}$$

Error STD

As a method of calculation, it can be expressed as the square root of the mean of the sum of the squares of the deviations of the data from the mean, as shown in *Eq. (4)*. The variance is the square of the standard deviation [49], [50].

$$\text{Error St. D} = \sqrt{\sum_{i=1}^{N}\frac{(x_i - \bar{x}_i)^2}{N-1}}. \tag{4}$$

In the equations (*Eqs. (1)-(4)*), N is the number of data, $\bar{x}$ and $\bar{y}$ are the average of the predicted and actual values, x_i and y_i are the predicted and actual values, respectively.

The confusion matrix is divided into four groups, as shown in *Table 2*. "True Positive" (TP), "False Positive" (FP), "True Negative" (TN) and "False Negative" (FN). In a successful model, there are no false positives or negatives [51], [52].

Table 2. Confusion Matrix.

		Actual Value	
		Positive	**Negative**
Predicted Value	**Positive**	TP (true positive)	FN(false negative)
	Negative	FP(false positive)	TN (true negative)

The following equation is used to perform performance evaluation calculations based on the confusion matrix (*Eq. (5)*). For more information on this formula, see the relevant references [52].

$$\text{Accuracy (ACC)} = \frac{TP + TN}{TP + TN + FP + FN}. \tag{5}$$

3.2 | Experimental Results

In this section we discuss the results of the proposed GFS models for detecting counterfeit banknotes. GFS has been used in combination with ML techniques to develop and test categorization models. These strategies have proven successful in categorization and are used extensively. Each model was validated ten times through cross-validation. *Table 3* summarizes the accuracy of the developed GFS models by class. To compare the performance of the proposed approach, the fuzzy/ANFIS network is additionally trained with GA counterfeit banknote detection algorithms. *Table 3* compares the classification results of the developed fuzzy, GA fuzzy, ANFIS and GA ANFIS models. *Fig. 4* shows the development of the training error values (RMSE) over 50 iterations of the approaches.

Table 3. Performance indices for proposed GFS model.

Models	MSE	RMSE	Error Mean	Error STD	Accuracy (%)
Fuzzy	0.033372	0.18268	-2,07E-13	0.18275	97.64
GA_Fuzzy	0.02403	0.15502	0.012779	0.15455	98.60
ANFIS	0.65563	0.80971	0.31436	0.74647	80.83
GA_ANFIS	0.031879	0.17855	0.0078403	0.17844	97.72

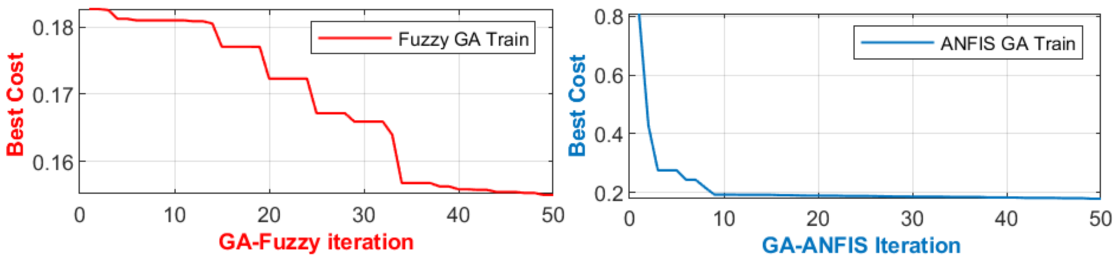

Fig. 4. Diagram of the best cost of the proposed GFS model.

Fig. 5 summarizes the classification performance obtained with the optimal parameter values derived from the simulation. The GA fuzzy model performed best here, with a classification rate of 98.6%. *Table 3* also shows the average performance of the categorization techniques and the percentage improvement compared to each other. When the GA method is used to train the ANFIS network, the classification performance increases by 20.9% compared to the regular ANFIS algorithm. It is found that the GA fuzzy classifier optimized using GA outperforms the classical fuzzy classifier by 0.98%. The improvements have shown that the GA increases the performance of the classifiers.

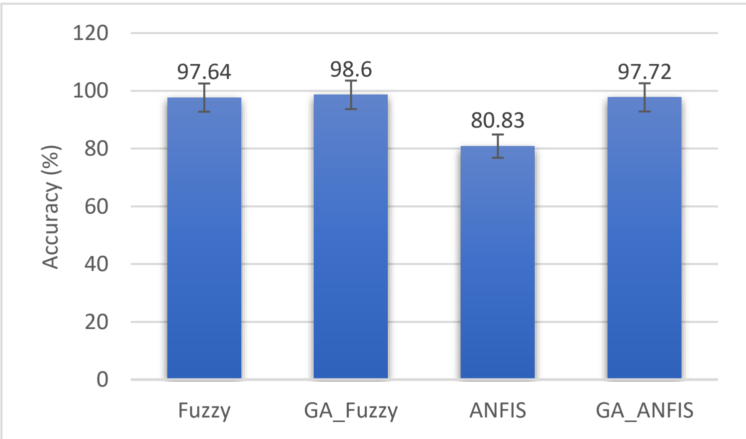

Fig. 5. Classification performance of the algorithms.

The performance metric used to evaluate the system in this case is the complexity matrix, which was discovered to be a measure of the correlation between predicted and observed values. The diagonal value of this matrix indicates the correct class, while the values outside the diagonal represent miscategorized elements. *Fig. 6* shows the confusion matrix of the proposed model.

The confusion matrix is used to analyze the results of a previously constructed classification model and to investigate errors in the mapping between real and predicted values during cross-validation. The positive and negative components in this matrix do not refer to accuracy or inaccuracy, but to the classes to be distinguished. Based on a dataset of counterfeit banknotes, this study created a model that attempts to predict whether the banknotes are counterfeit or not. When evaluating the results of the created

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classification model, TP, TN, FN, and FP are determined based on the matrix. TP and TN indicate the number of valid class predictions. FN and FP indicate how many inaccurate predictions the classes made in relation to each other. Here, the fuzzy classifier correctly predicted all counterfeit notes while it incorrectly predicted 32 non-counterfeit notes. The GA Fuzzy classifier has incorrectly predicted 19 non-counterfeit banknotes while it has correctly predicted all counterfeit banknotes. The GA_ANFIS classifier misclassified 30 non-counterfeit banknotes and misidentified 1 counterfeit banknote. The traditional ANFIS model, which has the lowest percentage of accuracy, incorrectly predicted 68 non-counterfeit banknotes while correctly identifying 186 counterfeit banknotes.

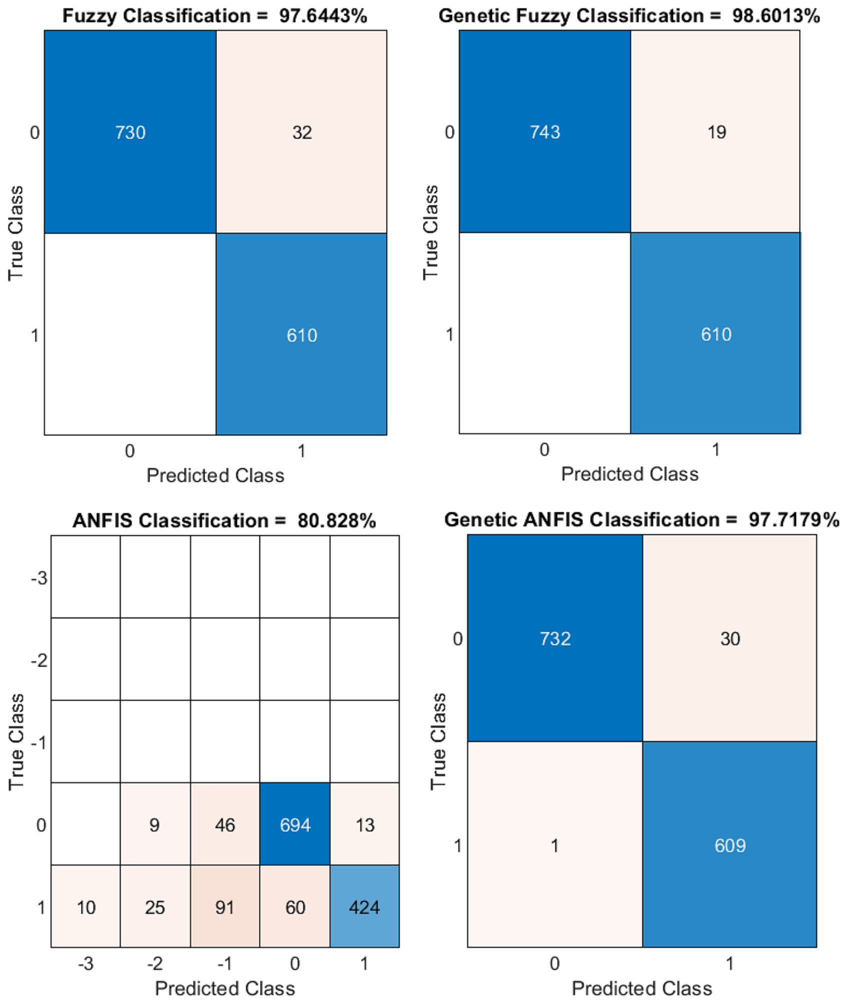

Fig. 6. Confusion matrix for detecting counterfeit banknotes.

4 | Conclusion

In this study, a method for detecting counterfeit banknotes based on a GFS is proposed. To classify the data of counterfeit banknotes, the fuzzy/ANFIS model was trained with the GA optimization algorithm and its performances were compared. From the results, it is found that the approach based on training Fuzzy and ANFIS with GA algorithm is more successful. It is shown that GFSs can be used to solve classification problems. GFS can be used in areas where ML algorithms need to be explainable due to the sensitivity of transactions. It was also found that the FIS network can be used in applications for various problems because the GA algorithm does not contain any constraints like derivative-based algorithms and can be easily applied to problems. According to the results of this study, the proposed GSF model was successfully applied in this theoretical study. Moreover, a practical application of this design seems to be possible. The method has a number of important advantages. It can distinguish genuine banknotes from counterfeit ones and thus prevent counterfeiting. The proposed model is fed with data from the counterfeit banknote dataset. Additional features that increase the discriminatory power of our system are currently being investigated. Furthermore, banknotes are susceptible to contamination due to their widespread distribution. It is certain that the degree of contamination varies from banknote to banknote. In addition, original banknotes may have defects and differ in appearance. Therefore, image-based categorization can provide more accurate results and can be applied in real time with real banknote photos and Deep Learning.

Data availability

The datasets presented in this study are freely available at [28].

Declaration of Competing Interest

The authors state that they have no known conflicting financial or personal interests that might seem to have influenced the work presented in this study.

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