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RESEARCH ARTICLE

A Deep Learning Framework for the Classification of Brazilian Coins

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ABSTRACT In this quickly developing world, automatic currency identification and recognition are crucial tasks. Several financial institutions, such as banks and hardware-based devices such as vending machines and slot machines, play an essential role in all monetary unification fields. Accurate coin recognition is essential in various contexts, including vending machines, currency exchange, and archaeological research. However, the distinctive visual characteristics of Brazilian coins, including variations in size, color, and design, pose significant challenges for automated classification. Most of the existing currency recognition systems are based on the physical properties of the currencies, such as length, breadth, and mass. At the same time, image-based methods rely on other properties like color, shape, and edge. This paper presents a novel deep-learning framework tailored to classify Brazilian coins. Our proposed deep learning framework leverages state-of-the-art convolutional neural networks (CNNs) to address these challenges. We introduce a Repetitive Feature Extractor Convolution Neural Network (RFE-CNN) model to recognize the currency faster and accurately. Our framework employs a multi-stage approach for coin classification. First, a pre-processing module handles coin localization and image enhancement to mitigate variations in lighting and background. Next, an RFE-CNN-based feature extractor extracts discriminative features from the coin images. We explore transfer learning from pre-trained models to enhance the model's generalization capability, given limited data availability. We used a comprehensive dataset of Brazilian coins, comprising various denominations, minting years, and conditions, to facilitate model training and evaluation. The dataset includes high-resolution images captured under diverse lighting and environmental conditions, ensuring robust model performance in real-world scenarios. In conclusion, our proposed deep learning framework offers a powerful and efficient solution for classifying Brazilian coins. The framework's adaptability makes it a valuable tool for recognizing coins from other regions with similar visual diversity and variability challenges. The proposed model has achieved a classification accuracy of 98.34% for the classification of Brazilian coins.

INDEX TERMS Brazilian coins, coin recognition, feature extraction, classification, model evaluation, convolution neural network.

I. INTRODUCTION

In this modern era, currency identification devices are crucial in all monetary sectors. In the case of Brazil, a country renowned for its rich cultural history and diverse coinage, the task of classifying Brazilian coins presents unique challenges due to the substantial variations in size, design, and appearance across different denominations and minting years. Currency recognition techniques may be used in coin-based printing devices, vending machines, automated

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toll gates, various bank hardware, etc., [1]. According to the prediction made by the International Chamber of Commerce (ICC), there will be a global financial loss of US $2.3 trillion by 2022 due to the exchange of fake currencies [2]. Due to the same issue, India also suffers from an economic loss of Rs 1.05 lakh crore every financial year [3]. Traditionally, coin classification has been manual and time-consuming, requiring expertise in numismatics and a painstaking examination of each coin. However, recent advancements in deep learning and computer vision have paved the way for automated coin classification systems that efficiently handle large volumes of coins with high accuracy. The classification of Brazilian coins presents a distinctive set of challenges. Unlike paper currency, coins are not uniform in size and color, and their designs evolve. Furthermore, factors such as wear and tear can further complicate the recognition process. These challenges necessitate a sophisticated and adaptable solution that can handle the intrinsic variability in coin appearance. An intelligent currency identification framework utilizing a convolution neural network has been proposed by taking motivation from this. The Brazilian coin dataset in the Kaggle repository has been used for model training and validation. The spare part of this paper contains a literature survey, a dataset description, and proposed model details, followed by a performance analysis and conclusion. The solutions for the problem mentioned above are mechanical, image-based, and electromagnetic techniques. Automated methodologies generally depend on attributes like mass, length, and thickness. But these methodologies only succeed when multiple currencies have the same physical properties. Based on the features identified, coins are categorized into different classes. In image-based methods, prediction depends on the design of the currency. This strategy includes two stages: the initial stage is snapping a photo of the money, and the subsequent advance is to contrast it with the reference currency dataset. The dataset has pictures of several coins taken by different angels. After that, for feature extraction, various image processing strategies like FFT [4], [5], Gabor Wavelets [6], DCT, edge detection, segmentation, image subtraction [7], and decision trees [8] are applied. The third electromagnetic technique addresses the material characteristics brought into the currency. As a result, if two coins are made of the same material, these tactics may fall short.

Our proposed deep learning framework is designed to address these challenges comprehensively. We introduce a robust and efficient approach for Brazilian coin classification to leverage the power of convolutional neural networks (CNNs), a subset of deep learning models tailored for image-related tasks. To facilitate model development and validation, we have compiled a comprehensive dataset comprising a wide range of Brazilian coin denominations, minting years, and conditions, ensuring that our model can handle real-world scenarios confidently. The framework is structured in multiple stages to ensure accuracy and reliability. First, a pre-processing module handles coin localization and image enhancement, effectively mitigating the impact of varying lighting conditions and backgrounds. Subsequently, our CNN-based feature extractor captures discriminative features from the coin images. Given the limited availability of labeled coin data, we investigate using transfer learning from pre-trained models to enhance the model's ability to generalize. To improve our framework's interpretability, we utilize the REF-based CNN model to extract the features uniquely, highlighting the regions of interest within the coin images that influence the classification decision. Furthermore, the model's performance is rigorously evaluated using a range of metrics, including accuracy, precision, recall, and the F1-score, both on the training and test datasets.

This paper showcases the effectiveness of our deep learning framework in accurately classifying Brazilian coins, providing not only high classification accuracy but also robustness to the diverse condition's coins may exhibit. Comparative analyses with existing coin classification methods underscore the superiority of our approach. Beyond Brazilian coins, the adaptability of our framework positions it as a valuable tool for recognizing coins from other regions, like Indian Coins, that share similar challenges related to visual diversity and variability.

II. LITERATURE SURVEY

As of my last knowledge update in September 2023, specific literature may not have addressed the "Deep Learning Framework for the Classification of Brazilian Coins." However, I can provide a general literature review on related topics such as coin classification, deep learning for object recognition, and numismatic research. Tajane et al. [9] have established a Deep Learning-based model using AlexNet to identify Indian coins. Here, the data sample consists of one, two, five, and ten-rupee coins and around 100 images of each class. Such fewer images give higher accuracy. On Indian coins, Chetan and Vijaya [10] devised a side and rotation invariant coin detection system. Here, segmentation was used to identify by rotating the image and utilizing the radius of the coins as a template; the coin prediction can be made. Modi et al. [11], on Indian coins, an ANN-based automatic coin recognition system was proposed. After the pre-processing and pattern averaging processes are completed, the feature vectors of the picture of size 20×20 are created. They used 70-coin pictures to generate 5040 images using various rotations. CNN might perform better in terms of classification accuracy. Reisert et al. [12] suggested a quick technique for coin recognition on the CIS benchmark dataset. Inverse bilinear interpolation addresses the tiny gradient changes in the input images. To improve performance, the feature function's FFT is also precomputed. These systems don't give higher accuracy. Capece et al. [13] created a deep learning-based coin detection system for mobile devices. This research employs five different models for five other datasets of Euro coins. Schlag et al. [14] constructed a deep-learning model to predict ancient Roman coins. Based on the cash condition, the coins are classified into three categories: very fine, delicate, and highly fine. In [15], the author proposed

TABLE 1. A brief presentation on state-of-the-art-works.

No.	Studies	Methodology	Merits	Demerits
1	Ref [9]	AlexNet	It provides lesser execution time and gives higher accuracy	The dataset contains only 500 images
2	Ref [10]	Side and rotation invariant coin detection system	Provides higher classification results	Longer execution time as various filters are used
3	Ref [11]	ANN	Easy to implement	Higher fault tolerance
4	Ref [12]	Inverse bilinear interpolation, feature function's FFT	Better classification of low-resolution images	Model complexity is higher
5	Ref [13]	MobileNet and AlexNet	Moile app by using Digit Rest API is created	Lower accuracy
6	Ref [14]	Very Fine, Fine, Extreme Fine based on the condition	Uses of Computer Vision give good results	The dataset contains low-quality images
7	Ref [15]	Image capture and preprocessing, including noise removal, feature extraction, classification, and recognition.	The software was developed for the recognition of currency notes	The average Recognition Rate is higher
8	Ref [16]	CNN with Keras trained a DL model as well as hosted a Flask-based web app on Heroku	Practical analysis of currency recognition with improved accuracy	Limited Scope
9	Ref [17]	DL model from VGG16, VGG19, Xception, InceptionV3, AlexNet, and ResNet50	Recognition is faster	Used fundamental concepts

the Saudi Paper Currency Recognition System using the Weighted Euclidean Distance approach. The system's four tasks are image capture, preprocessing, noise removal, feature extraction, classification, and recognition. On Indian currency paper notes, Swami et al. [16] applied the CNN model's Deep Learning technique. This paper represents a technique that is divided into two sections. Keras trained a DL model and hosted a Flask-based web app on Heroku. Bahrani [17] has presented a model that differs from frequently used neural network-based models such as VGG16, VGG19, Xception, InceptionV3, AlexNet, and ResNet50 regarding training and testing accuracy. The dataset contains all available Indian currency notes. The tabular form of the literature survey is shown in Table 1.

FIGURE 1. Dataset of Brazilian coins.

III. DATASET DESCRIPTION

The Brazilian coin dataset [18] is used in this effort to solve the problem. That contains 3059 images of 5, 10, 25, 50, and 100 (1 objective) centavos, as shown in Figure 1. Similarly, Figure 2 shows the Indian coin that each coin is unique in shape and design. An automated cropping technique with border detection is utilized here to avoid manually cropping images. Automatic cropping and boundary detection are performed to enhance the image visibility and clarity, which helps to improve model training. The cropping operation is being conducted with the following set of steps.

1. Edge Detection: The function performs edge detection on the input image using the Canny edge detection algorithm. This algorithm detects areas of rapid intensity change in the image, which typically correspond to the edges of objects.

2. Find the Largest Contour: The function uses 'cv2.findContours()' to find the contours (boundaries) of the edges detected in the previous step. It then identifies the shape with the most significant area, likely to represent the main object in the image.

3. Calculate the Bounding Box: The function calculates the bounding box of the largest contour found in the previous step using 'cv2.boundingRect()'. The bounding box is a rectangle that encloses the entire contour and is defined by

the (x, y) coordinates of its top-left corner and its width (w) and height (h).

4. Add a Margin: The function adds a margin around the bounding box to ensure that the cropped region includes some additional area around the detected object. This margin helps prevent cutting off parts of the thing that may be close to the edges of the bounding box. The size of the margin is specified by the 'margin' argument, which is the number of pixels.

5. Crop the Image: The function uses the adjusted bounding box (with the added margin) to crop the original image. It creates a new cropped image that includes the region of interest (the detected object) and the margin. This results in improving the visibility and clarity of the coin images. The dataset is split into two parts: the training set (2447-80% of samples) and the validation set (612-20%) inning and validation of Brazilian coin images are performed on an AMD Radeon R5 M330 machine.

FIGURE 2. Dataset of Indian coins.

IV. PROPOSED SYSTEM

A Repetitive Feature Extractor Convolution Neural Network (RFE-CNN) is used in this proposed work. An RFE-CNN is an advanced deep learning-based model that recognizes and classifies images [19]. Generally, currency classification based on handcraft factors like dimensions and color does not provide the best accuracy. CNN is used in a variety of applications, including character recognition [20], traffic signal recognition [21], [22], object prediction [23], [24], and so on. The proposed structure of the system is shown in Figure 3. The proposed model contains some novel approaches such as a customized Neural Network layers block is formed in this work, known as a Repetitive feature extractor. This block is mainly used as a feature map to reduce the number of features and identify the underlying pattern from the original currency image during classification. Initially, the system is trained and evaluated with the Brazilian Currency dataset. But in the next stage, to prove the customized model's robustness, it is trained and evaluated using the Indian currency dataset. In both cases, the model has shown a promising result in terms of classification accuracy. The model was fine-tuned during the experimentation using different hyper-parameters related to the Neural Network, such as other optimizers and different learning rates.

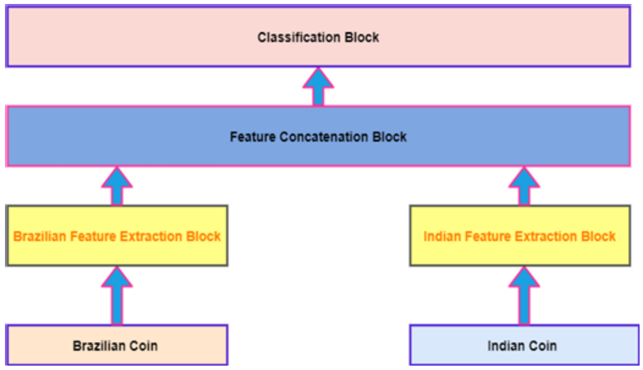


FIGURE 3. The structure of the proposed coin prediction system.

A. PROPOSED IMPROVED REPETITIVE FEATURE EXTRACTOR CONVOLUTIONAL NEURAL NETWORK

This RFE-CNN helps filter out the recognition pattern from the repetitive spatial information of an image. With deeper convolutions, the high-level feature becomes more exact and less redundant. In this proposed work, filters of size 3×3 are used because they are considered the smallest sized filter for extracting low-level features. It is impossible to discover the low-level information with a 1×1 filter as the size of the image, and the feature map remains the same after every convolution operation for the feature extraction from the input image, 16, 32, 64, 128, and 256 kernels/filters of size 3×3 used in every convolution layer, respectively. The same padding is used here, with a default stride of size 1, to ensure that the output is the same size as the input. This layer is primarily used for the successive size reduction of the input image, resulting in fewer number computations in the upcoming network layers. It generally performs max pooled or average pooled operations for spatial information reduction. In this proposed architecture max pool of size 2×2 is used after each convolution in the first 4 Repetitive Feature Extractor (RFE) blocks. In the 5th RFE block, the global average pooling layer is introduced after the convolution operation. The model contains five convolution layers, five pooling layers, and two fully connected dense layers. A max-pooling layer is used after each convolution layer, and a global average pooling layer is used after the last convolution layer. The activation functions that have been used are ReLU and SoftMax. The input image size is 240×320 for the feature extraction from the input image, 16, 32, 64, 128, and 256 kernels/filters of size 3×3 used in every convolution layer, respectively. The same padding is used here, with a default stride of size 1, to ensure that the output is the same size as the input. This layer is mainly used for classification after flattening an image. In this work 2, fully connected layers are used. The softmax activation function is

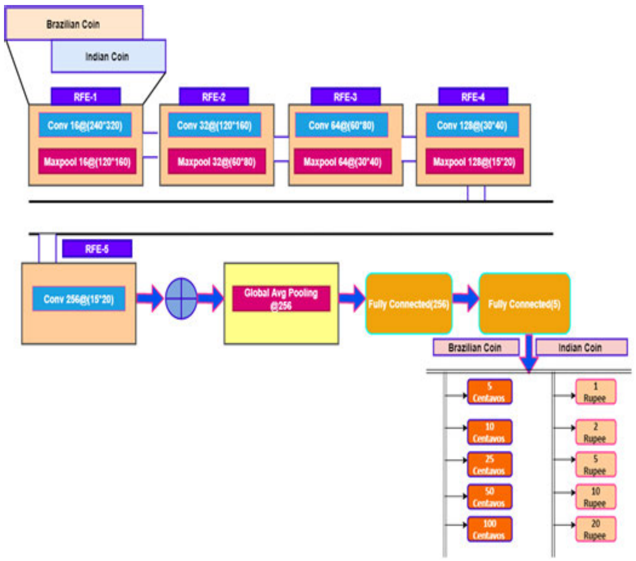


FIGURE 4. Proposed RFE-CNN architecture.

used in the last layer, whereas the ReLU activation function is used in the second layer. Figure 4 shows the proposed RFE-CNN architecture. Table 2 gives a brief description of the model parameters.

V. EXPERIMENTS

The model performance was evaluated by three commonly used metrics: sensitivity, precision, F1-Score and accuracy. The specificity represents the proportion of the negative samples that are correctly classified, the sensitivity is the proportion of the positive examples that are correctly classified, and the accuracy represents the ratio between the correctly classified samples to the total number of samples [32]. Their mathematical expressions are reference Eqs. 1 to 4:

$$\boldsymbol{Accuracy}\ (\boldsymbol{Accu}) = \frac{(\boldsymbol{True_{pos}} + \boldsymbol{True_{neg}})}{\boldsymbol{True_{pos}} + \boldsymbol{True_{neg}} + \boldsymbol{False_{pos}} + \boldsymbol{False_{neg}}} \tag{1}$$

$$\boldsymbol{Sensitivity}\ (\boldsymbol{Sens}) = \frac{\boldsymbol{True_{pos}}}{(\boldsymbol{False_{neg}} + \boldsymbol{True_{pos}})} \tag{2}$$

$$\boldsymbol{Precision}\ (\boldsymbol{Prec}) = \frac{\boldsymbol{True_{pos}}}{(\boldsymbol{True_{pos}} + \boldsymbol{False_{pos}})} \tag{3}$$

$$\boldsymbol{F1 - Score}\ (\boldsymbol{F1_S}) = \frac{\boldsymbol{2 * Sensitivity * Precision}}{\boldsymbol{Sensitivity + Precision}} \tag{4}$$

The model is assessed by utilizing distinctive optimizers like AdaMax [29] and RMSprop [24]. One of the significant explanations behind the exhibition supporting the model is the utilization of the Adam optimizer. Initially, the Adam optimizer uses its momentum term to update the weights faster. In the subsequent step, it corrects the direction towards

TABLE 2. Model structure and corresponding parameters.

Layer	Output Shape	Parameter
Conv2D_1	(240,320,16)	448
Max pooling1	(120,160,8)	0
Conv2D_2	(120,160,32)	4640
Max pooling2	(60,80,32)	0
Conv2D_3	(60,80,64)	18496
Max pooling3	(30,40,64)	0
Conv2D_4	(30,40,128)	73856
Max pooling4	(15,20,128)	0
Conv2D_5	(15,20,256)	295168
Global Average Pooling	256	0
Dense1	256	65792
Dense2	5	1285
Total Params:459685 Trainable Params:459685 Non-trainable Params:0		

global minima with the help of the scaling period responsible for scaling the performance and decaying the learning rate. The Adam optimizer is tested by tuning the learning rate. The model is trained and validated for 35 epochs.

A. ReLU ACTIVATION FUNCTION

The Rectified Linear Unit is half rectified [23]. When x is less than zero, f(x) is zero, and when x is greater than or equal to zero, f(x) is sufficient to x. The Mathematical representation of ReLU is shown in eq. (5).

$$\mathrm{f(x) = max(0, x)} \tag{5}$$

where, x is the input vector.

B. SOFTMAX ACTIVATION FUNCTION

SoftMax function activate neuron based on probability score [23]. It calculates probabilities of all neuron classes and produces a vector of that. The addition of the probabilities in the vector equals 1 for all possible classes. The Mathematical representation is shown in eq. (6).

$$\boldsymbol{S}\,(\boldsymbol{x})_{\boldsymbol{i}} = \frac{\boldsymbol{exp}\,(\boldsymbol{x_i})}{\sum_{\boldsymbol{x}=1}^{\boldsymbol{n}} \boldsymbol{exp}\,(\boldsymbol{x_j})} \tag{6}$$

where x is the input vector

x_i is i-th input vector element

$exp\,(x_i)$ is a standard exponential function

$\sum_{x=1}^{n} exp\,(x_j)$ is a normalization term.

C. ADAM OPTIMIZER

Adaptive Moment Estimation is an efficient optimizer mostly used for classification-based problems [24]. It combines the idea of the "RMSProp" [24] and the "gradient descent with momentum" [25] optimizers. The expressions for these are shown in eqs. (7) and (8).

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\frac{\delta L}{\delta w_t} \tag{7}$$

$$s_t = \beta_2 s_{t-1} + (1-\beta_2)\left(\frac{\delta L}{\delta w_t}\right)^2 \tag{8}$$

Since m_t and s_t have both initialized as 0, as both β_1 and β_2 become 1, they develop a tendency to be "biased towards 0". By calculating "bias correction" m_t and s_t this optimizer solves the problem. This is also done to keep the weights under control when they approach the global minima, preventing large oscillations as they get close. The momentum term and the scaling term are shown in eqs. (9) and (10).

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} \tag{9}$$

$$\hat{s}_t = \frac{s_t}{1-\beta_2^t} \tag{10}$$

where, m_t is the sum of gradients at a given time t (initially, $m_t = 0$)

s_t is the sum of the squares of previous gradients (initially, $s_t = 0$)

$\hat{m}_t$ is a bias correction term

$\hat{s}_t$ is a scaling term

β_1 and β_2 are decay rates of gradients ($\beta_1 = 0.9$ and $\beta_2 = 0.999$).

Where, intuitively adjusting to the gradient descent after each iteration so that the process remains regulated and unbiased, thus the name Adam. The bias-correction weight parameters m_t and s_t are now utilized instead of the standard weight parameters m_t and s_t. Putting things together in a general equation, as shown in eq. (11),

$$w_t = w_{t-1} - \eta\left(\frac{\hat{m}_t}{\sqrt{\hat{s}_t}+\varepsilon}\right) \tag{11}$$

where, w_t denotes the weights at a given point in time t

A. w_{t-1} denotes the weights at a given point in time $t-1$
   η is learning rate (0.001)
B. When $\hat{s}_t \to 0$, ε is a small +ve constant to prevent the "division by 0" problem (10)-(8).

D. SPARSE CATEGORICAL CROSS-ENTROPY

Here, the Sparse Categorical Cross-entropy Loss Function is used. The equation and results of this function are the same as for Multi-Hot Categorical Cross-entropy for more than two classes [26]. The Mathematical representation is shown in eq. (8).

$$Loss = -\sum_{c=1}^{C} y_i log\,(\hat{y}_i) \tag{12}$$

where, $\hat{y}_i$ is the i-th scalar value

y_i is the corresponding target value.

E. EXPERIMENT-1 (BRAZILIAN COIN PREDICTION)

In the proposed model we used a customized Neural Network layers block is formed in this work, known as a Repetitive feature extractor. This block is mainly used as a feature map to reduce the number of features and identify the underlying pattern from the original currency image during classification. Initially, the system is trained and evaluated with the Brazilian Currency dataset. But in the next stage, to prove the customized model's robustness, it is trained and evaluated using the Indian currency dataset. In both cases, the model has shown a promising result in terms of classification accuracy. The model was fine-tuned during the experimentation using different hyper-parameters related to the Neural Network, such as other optimizers and different learning rates.

TABLE 3. Results of different optimizers.

Optimizer	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
AdaMax	0.20	0.94	0.21	0.92
RMSprop	0.09	0.98	0.71	0.83
Adam	**0.02**	**0.99**	**0.06**	**0.98**

TABLE 4. Results of various values of learning rate.

Learning Rate	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
10^{-1}	1.61	0.20	1.61	0.17
10^{-2}	1.61	0.21	1.61	0.21
10^{-3}	**0.02**	**0.99**	**0.06**	**0.98**
10^{-4}	0.33	0.90	0.36	0.88
10^{-5}	1.37	0.47	1.37	0.47

The proposed framework has an accuracy rate of 98.27% during validation and 99.04% during the training process. The model is trained and validated for 35 epochs. The system's precision, recall, and f1-score are 98.43%, 98.45%, and 97.24%, respectively. The extremely low misclassifications made by the classifier as displayed in the confusion matrix [28], demonstrate its productive acknowledgment abilities as shown in Figure 5.

The Fig. 5 shows the confusion matrix presenting the performance of the model during its validation. The model is mainly trained using the Brazilian and Indian coin image dataset. Through the confusion matrix it is shown that how

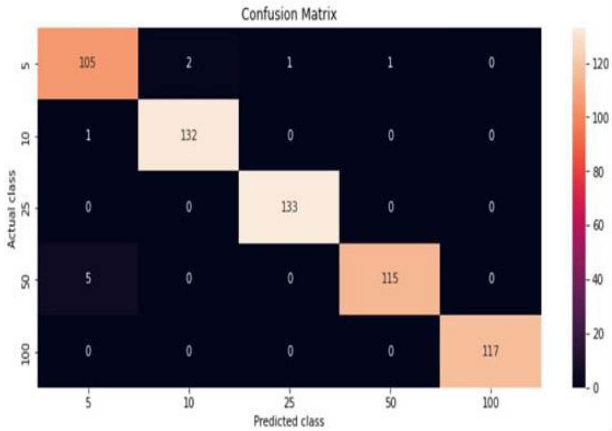


FIGURE 5. Visualization of confusion matrix with Brazilian dataset.

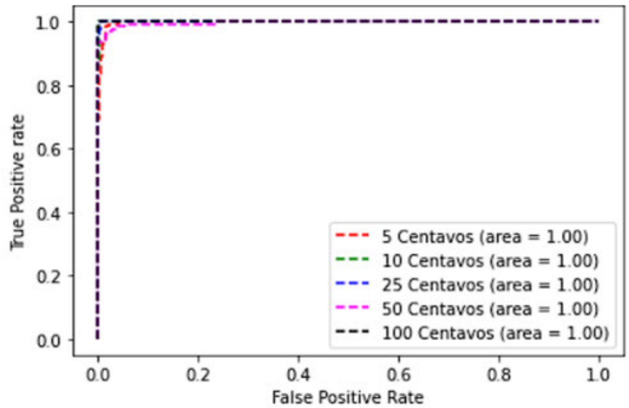
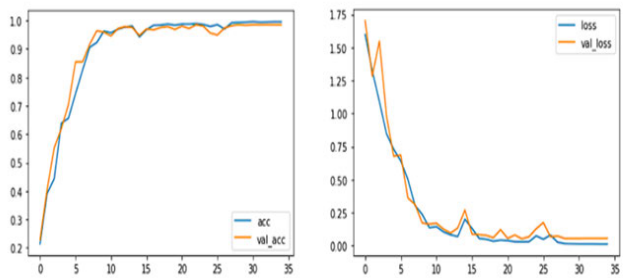


FIGURE 7. The receiver operating characteristic (ROC) curve of Brazilian coins.

the model has performed during the classification of different Brazilian and Indian coin using the unseen validation dataset. The good percentage of classification accuracy shows the efficiency of the model in classifying the unseen dataset. Hence this system only works for only Brazilian and Indian currency but not for other countries. But in future other country currency dataset can be integrated with the training dataset for enabling the system to classify or identify other countries' currencies also. The loss and accuracy curves of the model are shown in Figure 6. The figure shows that the training and validation accuracy and loss follow each other with next to no immense deviation. This demonstrates that the model isn't enduring overfitting and underfitting issues.



(a) (b)

FIGURE 6. Brazilian coin: (a) accuracy curve, (b) loss curve using the training and validation data.

Also, we have tested our proposed model with different hyperparameters like optimizers such as AdaMax, RMSprop, and Adam. The obtained performance using other optimizers is presented in Table 3 and Table 4 presents results of the proposed model with different learning parameters. Finally, the model's performance is determined by drawing the ROC curve [30]. It is a plot between the actual and false-positive rates at different thresholds. As shown in Figure 7, the AUC score obtained for every output class is 1.0. This proves the robust behavior of the classifier.

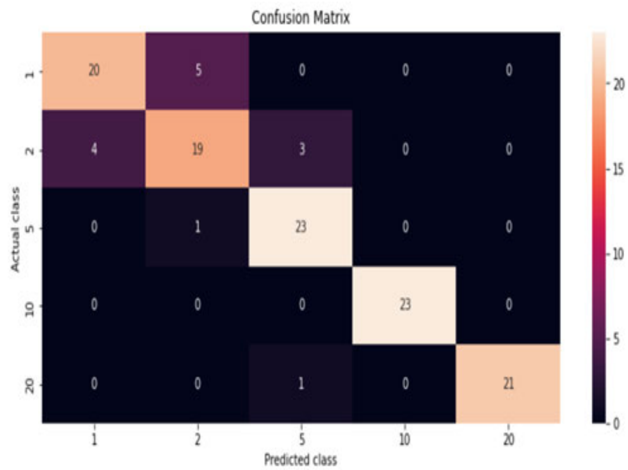


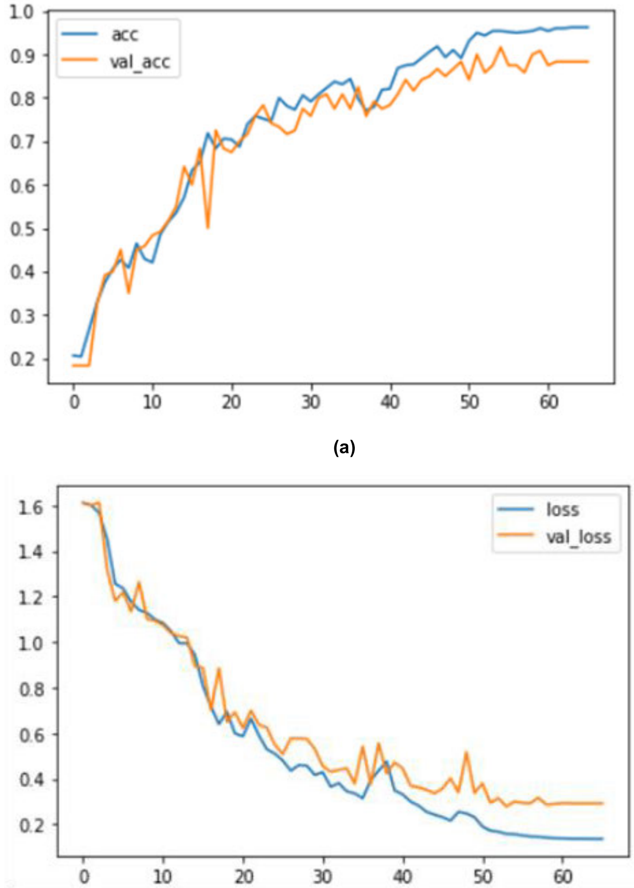
FIGURE 8. Visualization of confusion matrix of Indian coins.

F. EXPERIMENT-2 (INDIAN COIN PREDICTION)

We have also considered the Indian coins as input to the proposed model RFE-CNN to check whether the model is predicted effectively or not. The same architecture is deployed for predicting the Indian coins. The same hyperparameters were used for the Indian coin prediction experimental work. The reported confusion matrix is presented in Fig. 8. Training and validation accuracy and loss curve are shown in Fig. 9. Similarly, the ROC curve for Indian coin prediction is given in Fig. 10. The performance metrics results of the proposed model using two different datasets are presented in Fig. 11.

G. COMPARATIVE ANALYSIS

A comparative analysis of the proposed model is shown in Table 5. The consequences of the proposed classification method are compared with the existing similar such methods [33] accuracy is compared using five classifiers i.e., CSDA + LSTM, LSTM + LSTM + LSTM, LSTM, MLP and SVM classifiers. The comparative result analysis of five different classifiers is done and the reported more complicated. For the second paper [32], the performances



(a)

(b)

FIGURE 9. **Indian coin prediction: (a) accuracy curve, (b) loss curve using the training and validation data.**

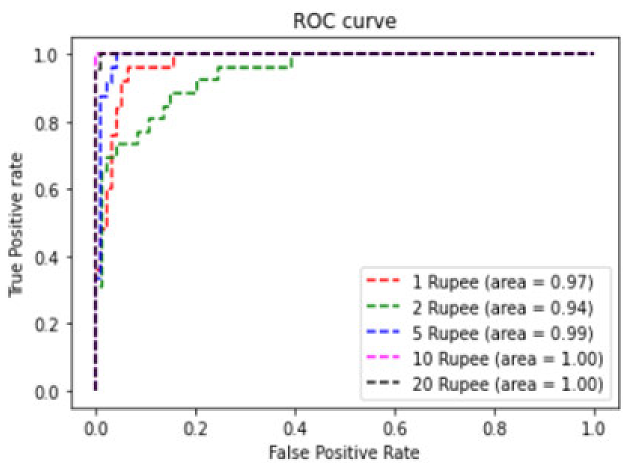


FIGURE 10. **The receiver operating characteristic (ROC) curve of Indian coins.**

are 87%, 71%, 63%, 66%, and 68%, respectively. It is clear from the table that the accuracy of the CNN classifier is 98%, with the newly proposed classification technique whereas, for the previously proposed classification technique, the

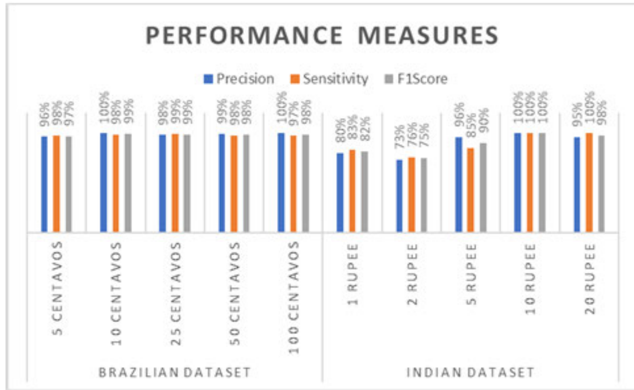


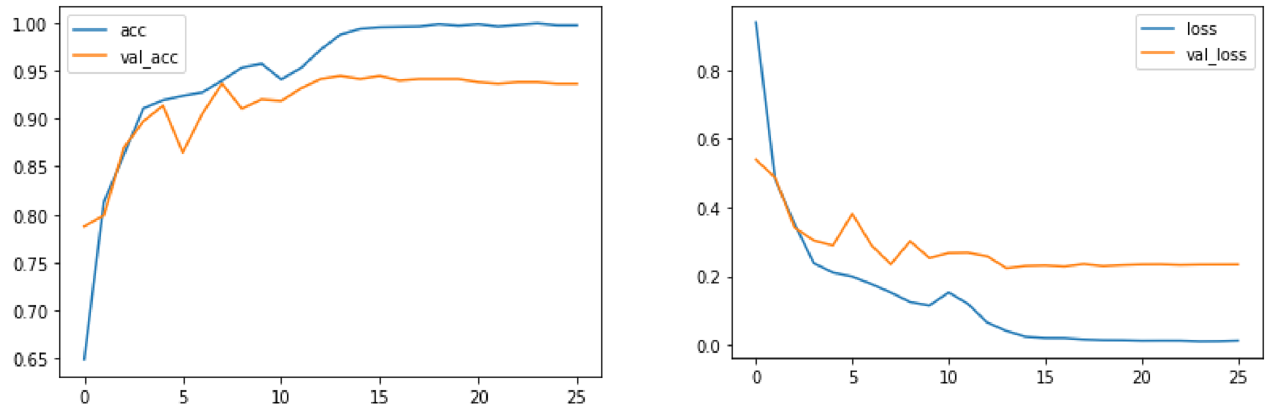
FIGURE 11. **Performance metrics results for both the Brazilian and Indian dataset.**

accuracy was 53% Ref [34] using LSTM, 57% Ref [35] using LSTM. From this classification results data, it is concluded that the newly proposed technique is giving better performance results than the technique used in [1], [36], [37], and [38]. This is because most of the existing techniques used traditional machine learning algorithms which highly feature dependents. Sometimes these explicit features are not suitable for all the cases. In the proposed classification technique, firstly we used deep learning concepts which help to discriminate the characteristics of the coin without using any types of explicit features. In the proposed methodology, the features are automatically recognized through the convolutional layer. Additionally, we also used different optimization techniques for better performance whereas, in the previous classification technique used in Ref. [31], the input image size is 100×100, and the proposed CNN model lacks depth. Here, the role of bagging and boosting techniques is not relevant. It only makes the mod deep learning model a preferable alternative because these ma-chine learning models do not always provide good accuracy in classification tasks. The accuracy has improved if the CNN model was utilized with different parameters tuning. The model's accuracy is 98%, which is significantly superior.

H. ABLATION STUDY AND GENERALIZATION TEST

This section describes the analysis of ablation study as well as generalization test on the model. Apart from the results analysis, this paper also conducted an ablation study on the various components of the proposed model. The main aim is to show the behavior of each of the components of the proposed model. For this, the whole model is divided into following modules:

- Model-1: In this model the proposed RFE-CNN is replaced by the ResNet50 [20] and rest of the model remains same. The purpose is to understand and analyse the behaviour of ResNet50.
- Model-2: In this model the proposed RFE-CNN is replaced by the VGG16 [20] and rest of the model



(a) (b)

FIGURE 12. Brazilian coin: (a) accuracy curve, (b) loss curve using the training and validation data using Resnet model.

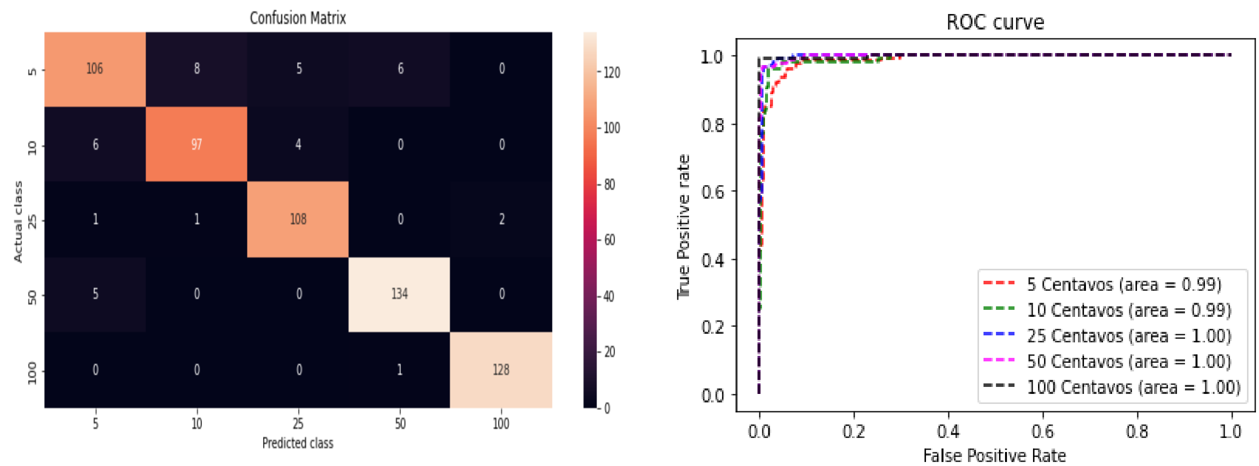
TABLE 5. Comparison with the state-of-the-art works.

No.	Author	Methodology	Problems & Solutions	Accuracy
1	Sharifi, A. M 2022 [34]	CDSA+LSTM LSTM+LSTM+LSTM LSTM MLP SVM	LSTM Epoch=100; Dropout=0.2; Loss=MSE; N=32; Activation=Tanh; Metrics= ACC CDSA P=20; Iteration =100; K=20; Speed=2 A=2, e=4, T=20, u=2 MLP Epoch=100; Hidden Layers=1; N=16; Activation Function= Sigmoid SVM C=1.0; Kernel= RBF; Degree=3; Gamma= 0; Coef=0.0; Tol=0.001	87% 71% 63% 66% 68%
2	Mayukh Samaddar 2021 [37]	ANN	linear and non-linear functions+ neural network algorithms	91.83%
3	Muppalaneni et al., 2021 [1]	CNN with Ensemble Learning method's bagging and boosting	The input image size is 100x100, the proposed CNN model does not have much depth, bagging and boosting techniques are not relevant	87%
4	Stefano Cavalli 2021 [39]	CNN	One Dimensional Convolutional Neural Network (1D CNN)	74.2%
5	Zheshi Chen 2020 [38]	Logistic regression SVM	Statistical methods including Logistic Regression and Linear Discriminant Analysis	66% 65.3%
6	Lv, L 2018 [35]	LSTM	long short-term memory (LSTM) neural network based on particle swarm optimization (PSO)	53%
7	Zhou, C 2016 [36]	SVM	PSO–SVM model	68%
8	Greaves, A 2015 [1]	Baseline Logistic Regression SVM Neural Network	blockchain-network based feature engineering and machine learning optimization	53.4% 54.3% 53.7% 55.1%
9	Madan, I. 2015 [36]	LSTM	LSTM Epoch=100; Dropout=0.2; Activation=Tanh; Metrics= ACC	57%
10	**Proposed Method**	**RFE+CNN**		**98%**

remains same. The purpose is to understand and analyse the behaviour of VGG16.

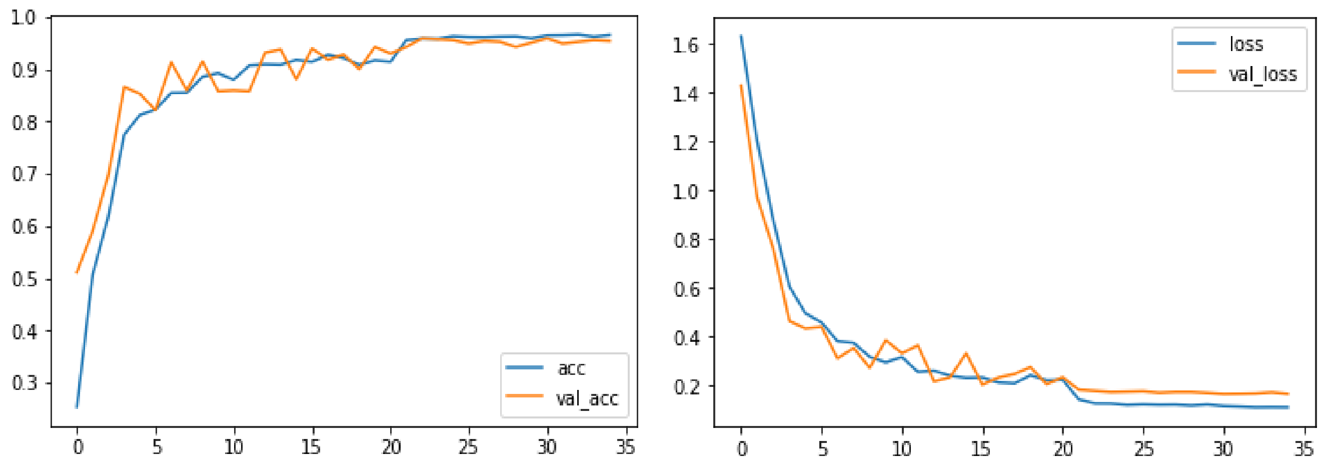
- Model-3: In this model the proposed RFE-CNN is replaced by the InceptionV3 [20] and rest of the model remains same. The purpose is to understand and analyse the behaviour of InceptionV3.
- Model-4: In this model the proposed RFE-CNN is replaced by the MobileNet [20] and rest of the model remains same. The purpose is to understand and analyse the behaviour of MobileNet.

Table 6 shows quantitative results analysis of aforementioned four models on the Brazilian coin dataset. Performance measures such as training and validation accuracy, precision, recall, f1-score and AUC score are used for performance comparison. The accuracies and loss curves obtained from ResNet, VGG16, inceptionV3 and MobileNet are presented in Fig. 12 (a-b), Fig. 14 (a-b), Fig. 16 (a-b) and Fig. 18 (a-b) respectively. The confusion matrixes and ROC curves of these models are also obtained and shown in Fig. 13 (a-b), Fig. 15 (a-b), Fig. 17 (a-b) and Fig. 19 (a-b) The



(a) (b)

FIGURE 13. Brazilian coin: (a) Confusion matrix, (b) ROC curve using the training and validation data using Resnet model.



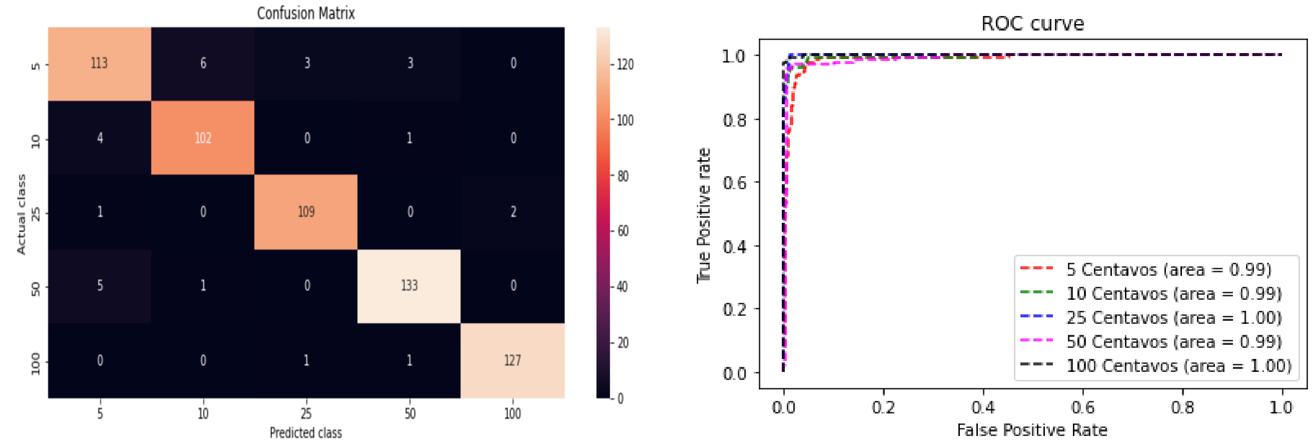
(a) (b)

FIGURE 14. Brazilian coin: (a) accuracy curve, (b) loss curve using the training and validation data using VGG16 model.

TABLE 6. Ablation study on the classification of Brazilian coins dataset using different pre-trained model.

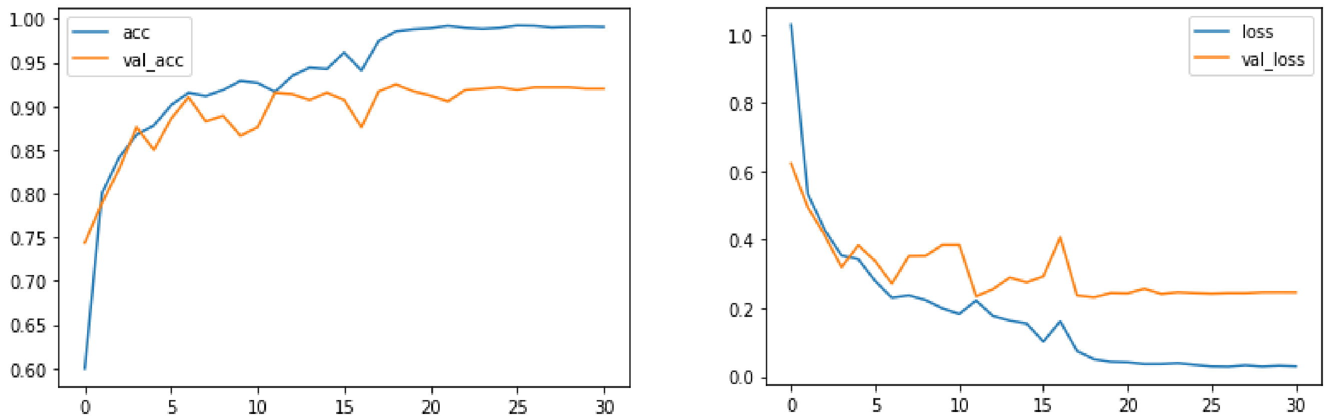
Model	**ResNet50**	**VGG16**	**InceptionV3**	**MobileNet**	**Proposed model**
Accuracy	0.9444	0.9591	0.9248	0.9575	0.9836
Precision	0.9342	0.9534	0.9173	0.9562	0.9800
Recall	0.9350	0.9543	0.9192	0.9544	0.9797
F1-score	0.9344	0.9538	0.9179	0.9541	0.9796
AUC score	0.9938	0.9944	0.9922	0.9969	0.9993

impact of ResNet (Model-1), VGG16(Model-2), InceptionV3 (Model-3), MobileNet(Model-4), are analyzed and it has got an accuracy of 94.44%, 95.91%, 92.48%, 95.75% and 98.36% which is less than the proposed model.



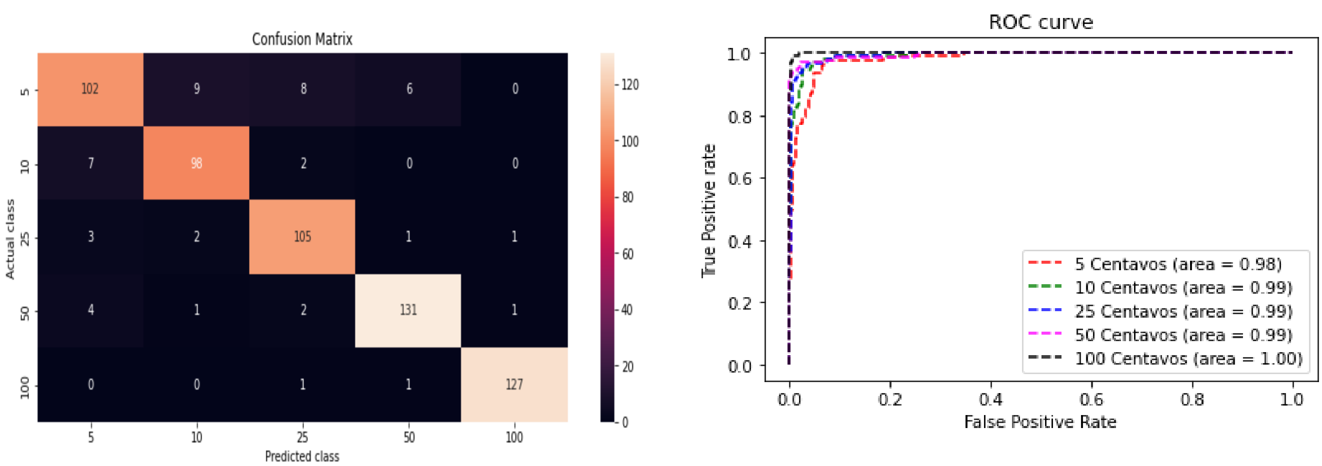
(a) (b)

FIGURE 15. Brazilian coin: (a) Confusion matrix, (b) ROC curve using the training and validation data using VGG16 model.



(a) (b)

FIGURE 16. Brazilian coin: (a) accuracy curve, (b) loss curve using the training and validation data using inceptionV3 model.



(a) (b)

FIGURE 17. Brazilian coin: (a) Confusion Matrix, (b) ROC curve using the training and validation data using inceptionV3 model.

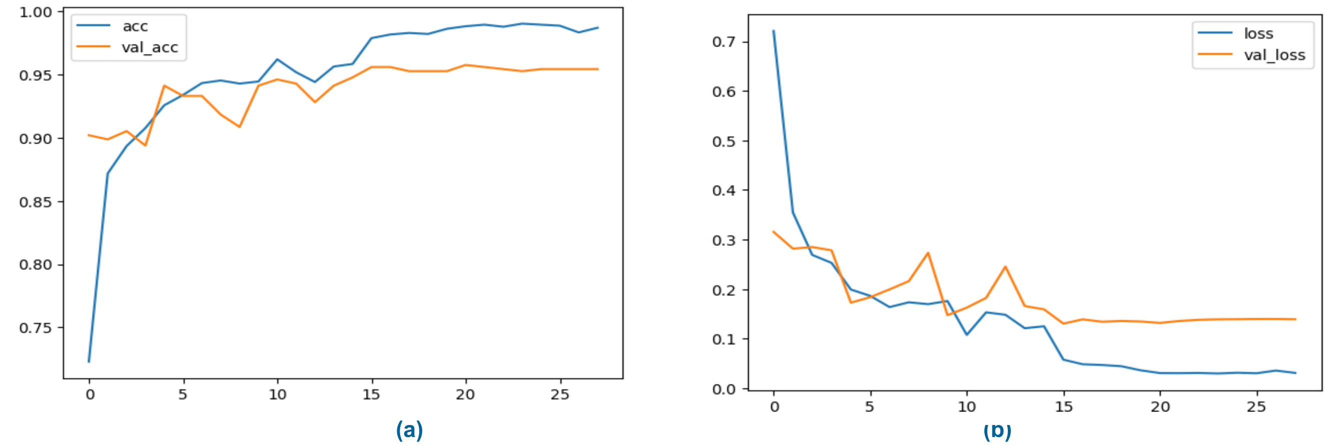


FIGURE 18. Brazilian coin: (a) accuracy curve, (b) loss curve using the training and validation data using MobileNet.

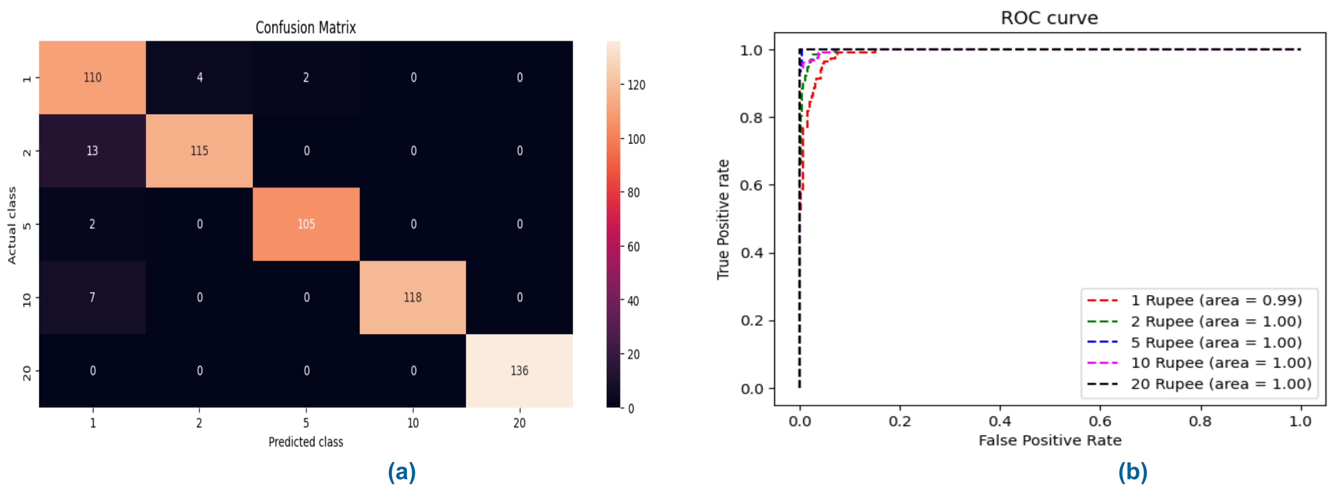


FIGURE 19. Brazilian coin: (a) Confusion Matrix, (b) ROC curve using the training and validation data using inceptionV3 model.

VI. CONCLUSION

In this study, we introduced a deep learning framework tailored to classify Brazilian coins, addressing the challenges posed by the visual diversity and variability inherent to this task. Our framework RFE leveraged convolutional neural networks (RFE-CNNs), transfer learning, and comprehensive datasets to achieve significant progress in accurately classifying Brazilian coins. The major strengths of the proposed model are Visual Variability, Transfer Learning, Comprehensive Dataset, and Interpretability The proposed method has shown promising execution as far as classification accuracy, precision, recall, f1-score, and AUC score are concerned. The parameter optimization has been done using the Adam optimizer. Using the ReLU activation function aided in attempting to avoid the vanishing gradient decent issue. Because of the blend of Adam and ReLU, the classifier has shown good accuracy during training as well as validation and assists with keeping away from overfitting and underfitting. The model has given a meager misclassification score that has helped the precision, recall, and f1-score, and the equivalent is likewise seen in the ROC curve. The experimental results demonstrated the effectiveness of our deep learning framework. We achieved a high classification accuracy of 98.34% on our test dataset, underscoring the model's capability to distinguish between different denominations, minting years, and conditions of Brazilian coins. This level of accuracy is promising and aligns with or surpasses similar studies in coin recognition.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper. On behalf of all authors, the corresponding author states that there is no conflict of interest.

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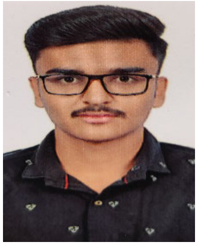

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