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Artificial Intelligence Model of Iraqi Paper Currency Detection in Vending Machines

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Abstract

The development of technology is becoming necessary in multiple fields that specialize in human interaction life. This has contributed to increasing awareness of electronic financial transactions enhancing by the ease of handling currencies, especially by employing vending machines in commercial markets and airports. Vending machines have become widespread nowadays, and due to their ease of use for customers, it has become necessary to pay attention to this type of device. Due to the different currencies adopted in countries around the world, there has emerged a need to increase the flexibility of programming these machines to be suitable for the countries using the devices. In this research, an intelligent convolutional neural network model CNN was built based on artificial intelligence techniques integrated with the Mahalanob distance method to embed the suggested "CNN-ThrMah" model. The dataset, which contains types of banknotes issued by the Central Bank of Iraq, was collected using digital scanning supplied by a high-resolution camera to achieve high accuracy. Then, the "CNN-ThrMah" model was built and trained on this data, using the optimizer "AdamW" to achieve a high level of accuracy in detecting the types of currencies for the tested data that the model had not seen. While a Mahalanobis-distance method is used to prevent the model from overfitting when generalizing in the real world. This model achieves high accuracy for all detections of all positive samples of Iraqi currencies and negative samples of non-currency items that contain currency from other countries.

Keywords: Artificial intelligence (AI); Convolutional Neural Network (CNN); Vending machines (VM); Mahalanobisdistance (Mah-dis).

1. Introduction

In recent years, the need for smart automation in everyday activities has led to major improvements in electronic financial transactions. Vending machines (VM) have grown a long way since they began as just simple coin-operated machines. Now, VMs are more complex, automated retail systems that are designed to be used in many kinds of financial transactions and can handle various types of cash from across the world. Modern vending machines not only give out items, but they also accept various payment methods, such as cash, credit/debit cards, and mobile wallets. This change has made vending machines more useful in a wider range of places and hasmade them easier for customers to use[1]. Efficient and secure handling of financial transactions is crucial to ensure smooth operation, prevent fraud, and enhance user .trust Incorporating hardware and software technologies like modern digital cameras, sensors, controllers, and computer vision processing makes it possible to enable real-time transactions, manage inventory, and analyze data in real time. All these techniques enable real-time transaction processing, inventory management, and data analytics, which collectively contribute to improved service quality and operational efficiency[2]. The combination of AI, IoT, machine vision, and electronic payment technologies is changing vending machines into smart, self-contained retail units[3].

Modern smart vending machines use powerful hardware, built-in controllers, and AI-driven algorithms to improve service quality, operational efficiency, and customer experience. Traditional machine learning techniques such as k-nearest neighbors**,** genetic algorithms, support vector machine (SVM) algorithms with controllers, and fuzzy systems have been utilized; these traditional techniques don't provide high accuracy when processing crimped or dirty banknotes[1]. Significantly, to enhance functionalities via multimodal fusion approaches, enabling vending machines to handle intricate stocks (e.g., electronic components) and optimize resource distribution by evaluating various sensor inputs and operational factors [4]. The technology for automatic recognition of currency notes is unique to each country, yet it may be used with standard banknotes from each country. One promising way to solve this challenge is to develop a system that can tell if a camera image of a cash note is false. Convolutional neural network models have been quite successful at classifying images. And figuring out if a dollar note is legitimate or phony from its picture is just a binary image classification task [5].

Digital payments are the most common way to pay in many cities, but being able to recognize and validate physical currency is still significant, especially in places where cash is still the main way to pay. AI-based algorithms include multiple types of convolutional neural networks (CNNs) versions, such as VGG16, MobileNetV2, and ResNet50 with attention mechanisms [6, 7]. In systems with limited resources, effective techniques like color-histogram matching provide viable alternatives for currency classification. These improvements ensurethat vending machines are still accessible to everyone, including people who aren't very tech-savvy and those who don't have access to them [8].

Several Iraqi currency recognition systems have been mentioned in the related work section; they are mostly dependent on convolutional neural network classifiers trained on small and carefully selected datasets. Although such systems perform well in a controlled setting, they are susceptible to unseen banknotes, partial occlusions, illumination variations, worn-out and damaged notes, and counterfeiting patterns, which are common in a vending machine setting. More importantly, however, is the fact that current systems lack a systematic mechanism for rejecting unusual and out-of-distribution inputs, which can result in fraud and economic loss. What is thus a critical research void is the fact that systems for Iraqi currency recognition must be capable not only of classifying known denominations but must also be able to reject unusual and unfamiliar banknotes as well. To overcome such a shortcoming, a hybrid CNN-ThrMah model is presented in this study, which combines feature extraction via deep CNNs and thresholding via Mahalanobis distances for accurate classification and efficient anomaly rejection.

2. Related Work

The researchers[9] integrate a method of K-Nearest Neighbors followed by image processing for enhanced counterfeit detection. Various techniques and methods are applied to the detection of fake currency based on the colors, width, and serial numbers mentioned. The proposed approach provides 99.9% accuracy for the fake identity of the currency. KNN succeeds in small datasets by achieving high accuracy, which hasled to increased use in computer vision processes. The CNN-based[10] recognition system for Bangladeshi banknotes, aimed athelping visually impaired ,people developed a new dataset that has been synthesized from more than 70,000 images of Bangladeshi currency. CNN models are built and trained using the samples from this dataset. The efficiency of this technique has been achieved through tested processes in various backgrounds. The average accuracy of detecting the eight kinds of Bangladeshi currency is about 92%. The researchers implemented a CNN–based model [11] to build a recognition system optimized for accessibility; the work concentrates on assisting the visually impaired in distinguishing among Iraqi banknotes. This paper suggests producing specific vocal commands that are equivalent to the categorized currency images and then informing visually impaired people of the denomination of each currency. In this paper, a dataset containing 3,961 image samples of the seven Iraqi paper currency categories was used. Finally, the model proves the feasibility of the proposed system with an accuracy of 98.6%. A deep learning model to detect Indian currency from these counterfeits was proposed[12]; which not only recognizes real and fake currency but also classifies it. Various pre-trained deep learning models, like VGG16, GoogLeNet, and MobileNet, were explored for currency classification and fake currency detection. These techniques were implemented on about 2572 samples of Rs images belonging to 6 denominations: 10, 20, 50, 100, 500, and 2000. The highest classification accuracywas achieved by VGG16 with accuracies of 98.08% and 97.95%, respectively. A method of synthesizinga dataset of Bangladeshi currencies: 5-taka, 10-taka, 20-taka, 50-taka, 100-taka, 200-taka, 500-taka, and 1000-taka, suggested by research [13], this dataset is called "BANGLADESHI BANKNOTE," which contains 8000 samples of images. The work modified AlexNet (M-AlexNet) for feature extraction from samples, where classification is followed by Multi Support Vector Machine (M-SVM). A mobile-friendly deep learning solution for multinational currency counterfeit detection uses smartphone cameras in a collected multi-country dataset covering both genuine and counterfeit notes of USD, Euro, KRW, and JOD. Then, it utilizes “you only look once, version 3” (YOLOv3) to detect and crop the banknote region. The CNN classifier is trained with three optimizers: stochastic gradient descent (SGD), Adam, and Sharpness-Aware Minimization (SAM). The last one receives an enhancement in generalization capabilities. This work was proposed by the researchers[14] who used various optimization techniques for CNN models to identify Ethiopian currencies by collecting a dataset from various Ethiopian currency samples with different ages and conditions. CNN models used in this paper include InceptionV3, MobileNetV2, XceptionNet, and ResNet50. The RMSProp optimization technique used with MobileNetV2[7], this model to achievesuperior accuracy of 96.4% in comparison to other CNN .models

A novel feature-based intensity calculation and classification approach is introduced[15], and the techniques of machine learning thresholding, K-means, and support vector machine (SVM) are used to find the fake currency based on intensity values. In this work, 50 samples of images were tested, which obtained an accuracy of 96%. The classification of currency using machine learning methods yielded better results compared to the existing approaches. SVM classifiers[16] for counterfeit detection weretrained on extracted image features such as color, shape, and texture patterns. Finally, the results of our experiment will demonstrate that the accuracy produced by the suggested method is about 99.55%. We also applied another supervised learning algorithm, Perception, to our dataset, and the accuracy was around 98.36%. A model[19] to identify the denomination and detect if it is real or not. The denomination of currencies is determined by using machine learning methods, such as support vector machines (SVM), decision tree classification (DTC), random forest classification (RFC), and K-NN (K-Nearest Neighbors), while using the AlexNet model to determine the currency's authenticity.

The proposed approach isclaimed to be fast and accurate, outperforming traditional methods. A new algorithm[8] for classifying three Nigerian paper currency notes_200, 500, and 1000_uses color histogram-based feature matching. It depends on HSI component images to extract features, while a lightweight currency classifier is designed to take advantage of variations in the histogram patterns to classify the paper currencies into the correct denomination class. The algorithm is fast in implementation over a testing dataset of 300 samples, with an average classificationaccuracy of about 98.66%. A model[18] that combines traditional image processing with CNN classifiers to detect counterfeit Indian notes. CNN effectively extracts visual features, such as color histograms and texture patterns, and feeds them to classification algorithms. The primary goal of this paper is to accomplish accurate detection and reduction of counterfeit circulation, contributing to the overall security of the economy. The accuracy of the proposed model is about 91.66% for all six security features in the Indian denomination of Rs. 500, 95.25% for all six security features in the Indian denomination of Rs. 200, and about 92.66% for all six security features in the Indian denomination of Rs. 100. A set of deep learning methods[19] for building models for thedetection of Iraqi banknotes, integrating preprocessing with these models to classify currency as either original or fake. The result is displayed on an LCD screen device. The experimental ,results in which the CatBoost model and SVM machine achieved a high accuracy of about 98%, while the accuracy of the CNN model equaled 99%. A sophisticated method of AI for detecting counterfeit money[20], which means using deep learning techniquessuch as CNN, VGG16, MobileNetV2, and Inception V3 as well as machine learning (ML) algorithms like Random Forest, Decision Tree Classifier, XGBoost, CatBoost, and Support Vector Machine (SVM) in addition to deep learning techniques like CNNs, VGG16, MobileNetV2, and InceptionV3, the paper builds a robust model to examine the security characteristics of Iraqi currency. All the models in our results had high accuracy rates, but they showed particularly strong performance with CNN, MobileNetV2, and Inception V3 equaling 0.99%, while CatBoost and SVM equaled 0.98%. A model for Jordanian banknote fraud detection[7] by integrating CNN with the channel attention model (CAM), utilizing a dataset from Kaggle that includes a collection of Jordanian banknotes in five different denominations. Thus, to make a significant contribution, while no paper has been published on Jordanian currency in any of its denominations, research can enhance the richness of the original dataset. The study achieved 96% accuracy, 96.6% precision, 96.4% recall, and a 94.5% F1 score. Additionally, the approach was tested on two datasets: the Indian dataset and the DS1, DS2, and DS3 datasets, and it obtained 88% and 99.9% accuracy, respectively. The achievement of detecting counterfeit Jordanian banknotes is proof that a well-established AI model contributes to addressing security vulnerabilities in many institutions. Microscopic imaging and high-resolution analysis[21] to enhance electronic financial transactions by detecting security features of Iraqi banknotes against originals. The authors used samples (10000, 25000) of Iraqi currency and worked to detect micro-level discrepancies, making it suitable for forensic validation. The results showed important differences and distinguishing marks in each sample, as each one contains a distinctive mark that can be detected. This approach can possibly be used to decrease financial currency counterfeiting crimes. Finally, AI-based classification[5] to detect counterfeit banknotes uses CNN with Recurrent Neural Networks (RNNs) approaches for the automated detection of counterfeit banknotes; the analyzed currency notes' image features by CNNs while RNNs were used to analyze security features such as serial numbers. The dataset of genuine and counterfeit currency notes (India) was used. This approach improves detection accuracy but is not specific.

3. Methodology

3.1. Dataset Synthesis:

In this work, a dataset was collected from scanners of 7 Iraqi currencies by two faces using the “iscanner” application on the digital camera of an iPhone 12 Pro Max with a resolution of 12 MP by activating the feature “Apple ProRow” in the camera option, which provides clearer images in DNG format. Then, these images were transferred to a computer to be converted to PNG format using Python program code to be more suitable for training the proposed model. Five images were taken from different angles of each side of all Iraqi paper currency samples. Iraqi currency contains 7 types, which are 50000 IQD, 25000 IQD, 10000 IQD, 5000 IQD, 1000 IQD, 500 IQD, and 250 IQD. Thus, the initial dataset contains 7 classes, with each having 10 samples for a total of 70.

After completing the collection of the dataset, our work focuses on how to augment this data to be suitable for building our model; therefore, the augmentation process needs to be applied to each class. In this work, 8 types of augmentation processes were performed: these are flip, small rotation (±15°), brightness/contrast jitter, optional blur, random crop-resize, and augmentation by 4 cut images through horizontal and vertical half-swaps. This augmentation for each sample. Thus, the augmentation process produced 630 samples as total augmented samples added to the original samples. Finally, the dataset contained 7 classes (with each class having 100 samples). All these images were resized to (128 x 128) to maintain a uniform size format for all samples, which represent the initial dataset. This dataset used images as the input for the proposed model. **Figure 1** shows some samples of the "final Iraqi paper dataset." The Iraqi paper currency dataset was collected by the author and uploaded to Google Drive; this dataset is linked in the repository named "Iraqi-Currency-Dataset" on GitHub. This dataset has been made available to researchers via this link: https://github.com/shamsalsabah/Iraqi-Currency-Dataset.

Figure 1. Some Samples of the "final Iraqi paper dataset"

After that, we collected a set of images that do not belong to the Iraqi currency and named this collection "non-currency." This set contains 150 samples; these samples differ in the types of other currencies from other countries and in different image samples that contain the same color levels as the levels in Iraqi currency. This dataset, which contains negative samples, doesn't need augmentation because it is used only in the validation and testing processes of the proposed model. **Figure 2** shows some samples of the "non-currency collection."

Figure 2. Some Samples of the “non-currency collection"

3.2. CNN Architecture:

In this research, a CNN model was built to detect Iraqi banknotes and distinguish them from non-currency images and from banknotes of other countries. In order to improve the performance of the vending machine and increase its use in commercial markets and airports in Iraq to provide fast and easy services to customers, a convolutional neural network model was developed. The CNN architecture is designed to be suitable for our samples, which are derived from RGB images and converted into feature vectors that the CNN model accepts as an input layer with dimensions of "128 × 128 × 3" channels. The resolution of the input image was kept constant at 128x128 pixels in order to strike a good balance between detail and processing speed. Iraqi banknotes have some minute discriminative regions like micro-patterns, numbers, and denominational textures, which are of utmost importance in recognition tasks. Higher resolutions would have increased memory and processing needs without any proportional improvement in performance; thus, 128x128 was considered to be an optimal and robust resolution for real-time implementation in vending machines. The CNN model is composed of three convolutional (Conv) layers to balance between accuracy and computation, capturing discriminative features before flattening and avoiding the risk of overfitting in the model. Blocks gradually increase the number of filters; each convolutional block extracts progressively more abstract features. These blocks are Conv Block 1 (32 filters); this block learns low-level features like edge types, textures, and basic colors. Conv Block 2 (64 filters) in this block learns mid-level features by combining low-level ones: corners, contours, and small object shapes. Conv Block 3 (128 filters) learns high-level features closer to semantics, such as object parts, shapes, or class-specific structures. These combinations of mid-level features help identify meaningful regions. All these blocks have a 3×3 kernel and the activation function ReLU to introduce non-linearity, followed by Global Average Pooling 2D to reduce spatial dimensions and emphasize salient features while integrating learned features for final classification. Then, the dense layer uses softmax to support denomination classification of 7 outputs. The model is built with the optimizer “AdamW,” which is an improved version of the Adam optimizer, with a learning rate (lr=1e-3). The use of the AdamW optimizer was preferred over the Adam optimizer since it decouples the weight decay from the update of the gradients. This is more beneficial in the Iraqi currency recognition task since the amount of available data is limited and the Iraqi currency has a large intra-class variability. The use of the AdamW optimizer will help in the generalization of the model. That rate is well-balanced as a starting learning rate: fast enough for convergence but stable enough to avoid divergence. The addition of weight decay (1e-3) prevents uncontrollable weight growth, thereby enhancing long-term stability. When dealing with classification problems, the standard loss function "cross-entropy" should be utilized. Utilize the standard loss function "cross-entropy," as it provides well-behaved gradients for optimization, which makes training stable and efficient. The proposed CNN model architecture can be seen in **Figure 3**.

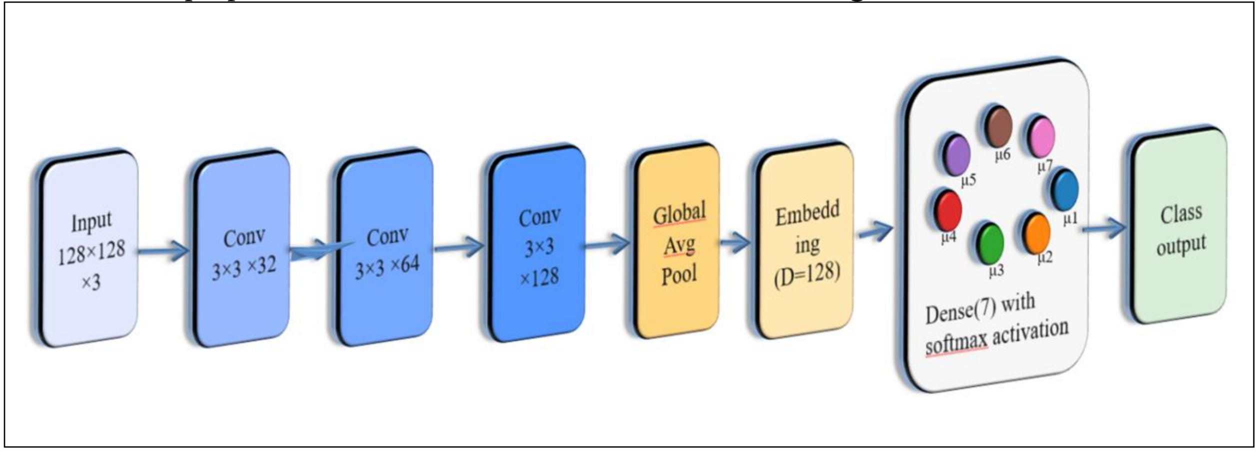

Figure 3. CNN Model Architecture

3.3. Mahalanobis Distance:

In neural networks, out-of-distribution samples remain a major problem in real-world scenarios, as these networks often find themselves processing samples that differ significantly from the samples during training. Several tools have been developed that aim to improve robustness and overall performance[22]. These tools focus on uncertainty and employ concepts that can be used in underlying mechanisms, such as softmax confidence, Bayesian learning, or ensemble methods to detect “out of distribution” samples. While there are tools that work in the representation space and employ concepts such as embeddings and Mahalanobis distance[23]. Mahalanobis distance (Mah-dis) is a statistical tool utilized widely in CNNs because it only considers samples from the correct probability manifold and ignores novel and forged notes, even if the CNN has strong confidence[24]. This distance outperformed the Euclidean distance in CNN models because the variables' anisotropic, correlated distribution in currencies is accurately measured by Mah-dis, illustrating statistical dissimilarity in distribution, while Euclidean distance considers an inappropriate spherical geometry and an inability to identify out-of-distributions and forgeries. Mah-dis can be expressed as the distance measure for a point, or it can function as a mechanism for measuring the distance between a set of distributions for a distinct class. This distance gives equal importance to all variables, considers all variable correlations, and normalizes all variables based on their respective variances. Therefore, it is highly beneficial for multivariate anomaly detection, out of distribution classification, and segregation in overlapping distributions[25].

4. Experimental Results and Discussion

In this research, a smart model was built to detect Iraqi banknotes and classify them from no currency images and from other currencies from other countries. A model of the convolutional neural network was built to be suitable for our dataset. The final dataset that contains positive classes of Iraqi currency after the augmentation process contained 630 samples; this number of samples is suitable to achieve a constant rate of models: 70% for training and 30 % for testing, while the validation process is achieved by taking 20 % from the training pool. Thus, the dataset is split into three sets: set1: 352 samples used in the training model; set2: 89 used in the validation process of the model; and 189 samples used in the test model. While the non-currency dataset, which contains 150 samples, is split into two sets (set 1 contains 50 samples used to set the threshold for the model probabilities generated during the validation process, while set 2 contains 100 samples used in a real test of the model). The proposed CNN model is trained with this training dataset using an input vector of 128 x 128 x 3, while we address RGB color images of size 128 x 128. The proposed CNN model is trained with 3 convolution blocks with increasing filters as follows: (32, 64, 128) model is trained with the optimizer "AdamW," a learning rate (lr=1e-3), and weight decay (1e-3); the output feature map has the same spatial dimensions (height and width) as the input when the stride equals "1" and zero-padding is used in all blocks. The model is trained with a batch size of 16 and continues until a maximum of 50 epochs, but the best model is selected based on performance starting from epoch 5. In each epoch, check if the model shows enhancement in performance, which depends on the validation loss (val_loss) and the validation accuracy (val_accuracy). Training progress begins with initial accuracy at epoch 1, which is about 13.6% with a high loss (~1.95). Accuracy and loss improved steadily; the training model in epoch 28 achieved the best val_loss = 0.05441 with val_acc = 99.51%. The training model's epoch results can be shown in **Table 1**.

Table 1. Result of training the proposed CNN model

Epoch	Train Acc.	Train Loss	Val Acc.	Val Loss	Best model
1	0.1358	1.9507	0.1236	1.9412	True
2	0.1378	1.9345	0.1124	1.9729	False
3	0.1966	1.8681	0.6966	1.6875	True
4	0.4703	1.5882	0.5169	1.0934	True
5	0.6031	1.0923	0.9888	0.6411	True
6	0.9447	0.5714	0.9101	0.4736	True
7	0.9031	0.3652	0.9213	0.344	True
8	0.8387	0.4288	0.9101	0.2929	True
9	0.9531	0.2517	0.8315	0.4871	False
10	0.8826	0.3033	0.7865	0.4285	False
11	0.8637	0.3447	0.7865	0.2673	True
12	0.96	0.2254	0.8764	0.2324	True
13	0.9455	0.1747	1.0000	0.1933	True
14	0.9776	0.1486	0.9663	0.1353	True
15	0.9259	0.1659	0.9551	0.1282	True
16	0.9591	0.1247	0.9888	0.108	True
17	0.9884	0.097	0.9775	0.1137	False
18	0.9676	0.109	1.0000	0.1351	False
19	0.9902	0.0852	0.9551	0.0977	True
20	0.9856	0.0831	1.0000	0.1037	False
21	0.9091	0.2572	1.0000	0.1296	False
22	0.9595	0.1202	0.9551	0.1324	False
23	0.9333	0.1722	1.0000	0.0903	True
24	0.9803	0.0779	0.9213	0.2134	False
25	0.9392	0.1471	1.0000	0.1021	False
26	0.9909	0.0815	0.9213	0.1562	False
27	0.9651	0.1056	1.0000	0.0784	True
28	0.9951	0.0436	1.0000	0.0544	True
29	0.9969	0.036	0.7865	0.336	False
30	0.9367	0.1432	0.9888	0.1096	False
31	0.9936	0.0481	0.9888	0.0809	False
32	0.9703	0.0862	0.8764	0.1904	False
33	0.9361	0.1332	0.9551	0.1672	False

The proposed model implemented a training process using Python programming with Spyder version 6.0.5. This program was installed on an ASUS laptop computer, system_model: "ROG Zephyrus M16 GU604VI_GU604VI", with processor "13th Gen Intel(R) Core(TM) i9-13900H

(20 CPUs), ~2.6GHz", hard disk SSD "250 GB," and memory RAM "32 GB." This computer model is supported by GPU model: "NVIDIA GeFORCE RTX 4070, "8GB". The accuracy and loss function ratios of the proposed model during the training and validation processes can be seen in **Figure 4**. The performance of the proposed CNN model can be checked by calculating four types of metrics in addition to accuracy and testing the proposed CNN model on test data that contains 189 divisions for 27 samples for each class; these metrics are: Precision, Recall, and F1-score. The values of these metrics for each class in the testing process are shown in **Table 2**.

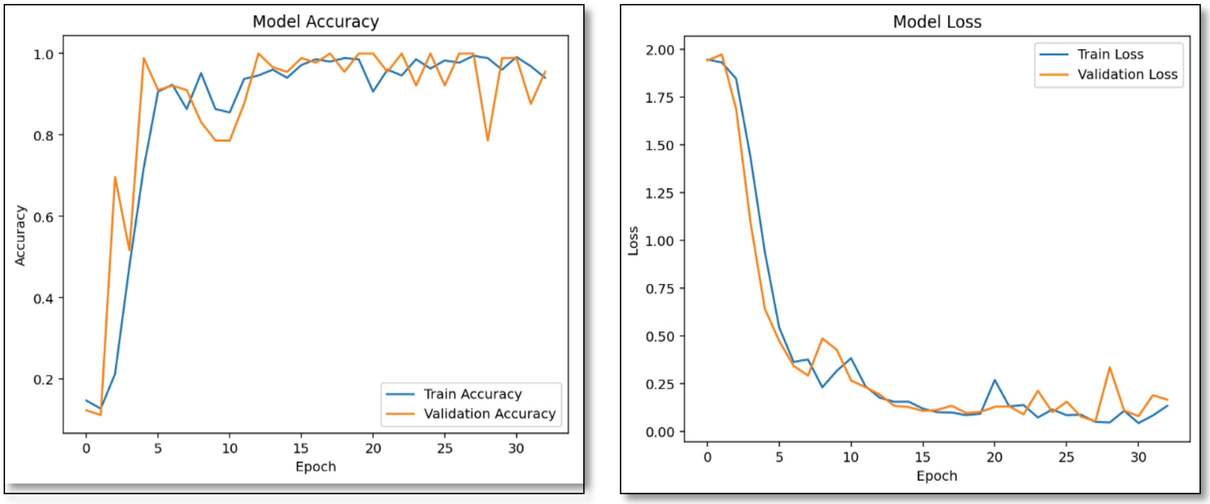

Figure 4. The accuracy and loss function ratios of the proposed CNN model during the training and validation processes

Table 2. Metrics of Performance of testing Process

Class	Precision	Recall	F1-score
250	1.00	1.00	1.00
500	1.00	1.00	1.00
1000	1.00	1.00	1.00
5000	1.00	1.00	1.00
10000	1.00	1.00	1.00
25000	1.00	1.00	1.00

When this model achieves classification for all positive samples perfectly, with extremely low losses, no observed misclassifications, and high agreement between predicted and true labels, the proposed model was evaluated on “non-currency” samples at a SoftMax confidence threshold of 0.6, at this threshold, the model rejected only 12.50% of images that are labeled “non-currency.” Therefore, embedding the output of the CNN model needs a method that finds classes according to the criteria of convergence between the probabilities of the resulting samples. Mahalanobis distance was suggested to find the convergence between the probabilities of the positive classes and isolate them from other probabilities to make the model succeed in evaluation on a completely independent dataset with different capture conditions. The process of including the proposed model to a suitable threshold that separates currency classes from “non-currency” is called the embedding process of the model. This process is implemented using the Mahalanobis distance (Mah-dis) method due to its efficiency in separating multiple convergent possibilities and finding a suitable threshold for the training model. Samples of positive currency categories were used with set 1 of negative samples, which were used in the validation of the model.

The Mahalanobis distance applied during the embedding process tunes a Mahalanobis threshold (Mah-thr) and suggests a value of approximately "17.26" for this threshold. Finding the appropriate threshold according to the embedding process of the proposed model is shown in **Figure 5**.

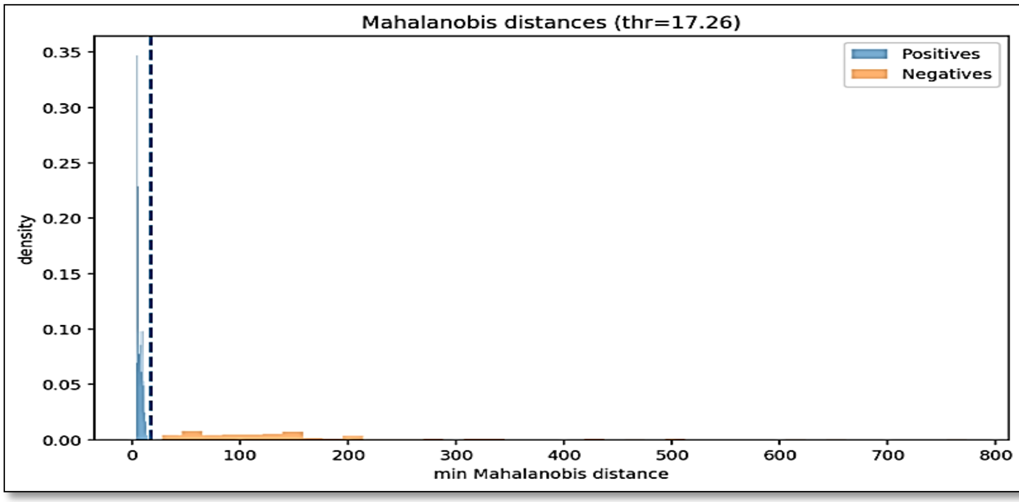

Figure 5. Threshold of sample classes by CNN model

After the completion of the embedding process of the suggested model, the name of this model proposed in this research for detecting Iraqi currencies in vending machines is “CNN-ThrMah,” which is the embedding model process of Mahalanobis distance in tune with the appropriate threshold for the generalization model to work. The “CNN-ThrMah” model was tested on 200 unseen samples (100 currency and 100 non-currency). These samples were considered unseen data for the model, and the results of the detection model, the confusion matrix of per-class performance for the “CNN-ThrMah” model build, and the normalized testing result are shown in **Figure 6**. The confusion matrix shows that the “CNN-ThrMah” model achieves 100% accuracy in testing the selected real data.

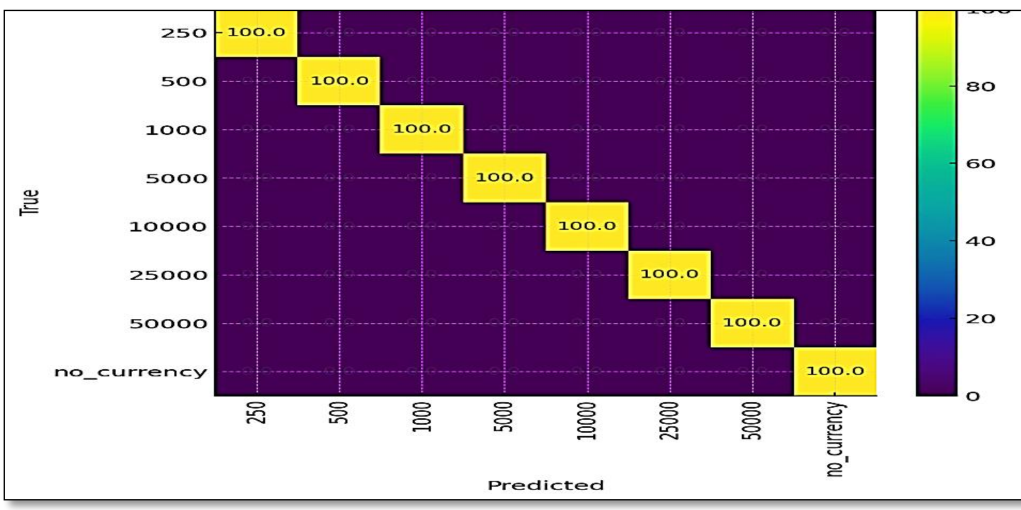

Figure 6. Confusion Matrix of per-class performance for “CNN-ThrMah” model

The “CNN-ThrMah” model, which was proposed in this research, was compared to previous studies [11, 20, 21] that dealt with detecting Iraqi currencies. The “CNN-ThrMah” model is considered more efficient in terms of the type of samples, the methods of collecting samples, and the number of typical positive and negative samples, which makes the model faster in the training process, and the method of handling model overfitting, which allows the “CNN-ThrMah” model to generalize on real samples of data, and this has caused high accuracy in its tests. This performance comparison can be shown in **Table 3**. Though the “CNN-ThrMah” model proposed in this research obtained a 100% accuracy rate for the unseen test images, the issues of possible overfitting and actual variability in the real world still apply. The use of the Mahalanobis distance thresholding method ensures a simple way of determining when the banknotes go out of distribution or when they can be termed as outliers, thereby avoiding the problem of being forced into a classification for unknown or irregular banknotes. In actual applications, such as in a vending machine, the system will not classify uncertain images, which helps avoid the problem of misclassification. Additionally, further robustness can be obtained through the use of a larger training set that may comprise actual and artificially created degraded images, thereby opening a promising research path.

Table 3. Performance comparison with other similar approaches

Paper (year)	Type of Model	Type of Camera	Type of Currency	No. of Samples	Acc.	Generalization
In (2022) [11]	Custom CNN with 19-layer	Digital camera	Iraqi dinar, 7 classes	3961	98.6%	No test on real data
In (2024) [20]	Variety models	Digital camera	Iraqi dinar, 7 classes	1087	99.26%	No test on real data
In (2025) [21]	No use model.	Microscopy	Iraqi dinar, 2 classes only	Not determine	No metrics	No model
Suggest CNN-ThrMah model	Custom CNN integrat with Mahalanobis-distance	Mobil Digital camera with high resolution	Iraqi dinar, 7 classes	680	100.0% of test sample	Test real data

5.Conclusion

The development in vending machine technology that integrates artificial intelligence techniques with sensors and controllers, which increases the use of computer vision processes in the industry, has made it necessary to pay attention to this type of device and design an intelligent model capable of accurately handling the currency in each country where a vending machine is found. In this paper, the researcher adopts the idea of building a specialized model to detect Iraqi currencies, which are of seven types (50000 IQD, 25000 IQD, 10000 IQD, 5000 IQD, 1000 IQD, 500 IQD, and 250 IQD). Also, the researcher took into account the limited samples of data available, so various preprocessing and augmentation methods have been adopted to increase the number of samples needed to build the model. The proposed model, called “CNN-ThrMah” suggests building a CNN and then tuning the output by using a calibration threshold, a threshold of the model using the Mahalanobis distance method to embed a Mahalanobis threshold (Mah-thr) in the model. The Mahalanobis distance method is used to prevent the model from overfitting when generalizing in the real world. In this model, “Mah-thr” equals 17.26, which keeps 100.00% of the tested samples classified as positive and negative rejection at this threshold, also 100.00%. This model achieves high accuracy for the detection of all positive samples of Iraqi currencies and all rejected negative samples of non-currency samples, which also contain currencies of other countries. While this study focuses on Iraqi currency recognition, the researcher suggests a set of future work which is: extending the CNN-ThrMah model to multi-currency recognition (e.g., USD, EUR, and neighboring regional currencies) to evaluate cross-currency generalization, deploy the model in real vending machine prototypes to assess performance under realistic conditions such as motion blur, lighting variation, and mechanical banknote handling, integrate OCR-based serial number verification to enhance security, traceability, and counterfeit detection. Finally, optimize the model for real-time embedded hardware used in vending and ATM systems.

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Conflict of Interest

The authors declare that they have no competing interests in this work.

Author's Contribution

This paper proposes a CNN model specialized in detecting Iraqi currency in vending machines. This model can increase the performance of these machines and enhance their use in marketing and airports in Iraq. While these places are considered crowded with people, the proposed model is developed to prevent overfitting of unseen data by embedding an appropriate threshold Mahalanobis distance.

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