Develop a Robust System for Detecting Counterfeit Iraq Currencies Based on Deep Learning Techniques

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ABSTRACT
Counterfeiting poses a serious threat to the financial economy because advanced counterfeit banknotes, thanks to advances in printing technology, have become difficult to identify through traditional investigation techniques. Maintaining the security of international economic systems and keeping pace with evolving counterfeiting strategies requires continuous study and development in this field. The Central Bank of Iraq is the exclusive management responsible for issuing local currency, so verifying the authenticity of Iraqi currency is of utmost importance to maintain the integrity of the country's financial economy. This thesis aims to develop a reliable system for detecting counterfeit Iraqi currency that can distinguish the subtle differences between real and counterfeit Iraqi currency. This work utilizes machine learning algorithms such as Random Forest, XGBoost, Decision Tree Classifier, Support Vector Machine (SVM), and CatBoost. In addition, deep learning models such as Convolutional Neural Networks (VGG16, InceptionV3, MobileNetV2) were employed to allow counterfeit banknote detection with high accuracy and reliability.The proposed system was trained on a dataset of 1359 images that include two types of Iraqi currencies (real and counterfeit with the highest level of professionalism) and in different categories, as they were collected in cooperation with the Central Bank of Iraq after obtaining official approvals from the relevant authority. The dataset underwent initial processing using augmentation and annotation techniques to increase the dataset number to improve the network's performance in the training process concerning prevalent feature extraction and thus achieve high detection accuracy, becoming 4188 for real currencies and 3966 for counterfeit currencies. The dataset was divided into 80% for training and 20% for validation. In this work, a real-time system was built and implemented based on a set of main components including Raspberry Pi5, Raspberry Pi camera, servo motor, and LCD screen. The device discovers the Iraqi currency using a camera and a servo motor supported by UV light to capture the currency image to ensure the highest clarity and accuracy. The image is sent to pre-trained deep learning and machine learning models to classify it as counterfeit or real. Finally, the detection result is displayed on an LCD screen. The experimental results in which CatBoost and SVM were used showed an accuracy of up to 98%, while the accuracy of the CNN model ranged to 99%. These results demonstrated the effectiveness of advanced technical solutions in thwarting the risks posed by counterfeit money, protecting the financial economy, and reducing losses.

Keywords: Counterfeit Detection, Iraqi Currency, Machine Learning, Deep Learning, Convolutional Neural, Networks (CNN), Currency Recognition System, Financial Security, Banknote Authentication

1. INTRODUCTION

Fake currency poses a major threat to global financial systems and economies. Counterfeit currency notes obtain dire consequences such as financial instability, decreased trust in financial institutions, and significant economic losses. Consequently, it leads to financial and economic losses for individuals, and commercial and industrial companies due to a lack of confidence in dealing with financial institutions [1]. With advancements in printing technology, creating counterfeit money that closely resembles genuine currency has become easier, Traditional methods of detecting counterfeit money often rely on human expertise, which can be time-consuming and prone to error. complicating the manual identification of fake notes [2].

Because defrauding and exploiting forged banknotes continue to rise, conventional methods of fake currency detection which often depend on human expertise, take up a considerable amount of time and are not accurate; leading to the development of detection systems through employing artificial

intelligence methods and algorithms. While money-counting machines equipped with sensors like magnetic, infrared (IR), and ultraviolet (UV) sensors are employed, their high implementation costs and susceptibility to noise limit their widespread adoption [3]. Despite technological advancements, the rate of counterfeiting has increased. In 2015, approximately 70% of the $78 million in counterfeit currency circulating in the U.S. was produced using digital printing technologies [4].
Traditional Machin Learning techniques such as k- nearest neighbor, genetic algorithms, and fuzzy systems were being used, these traditional solutions tend to yield lower accuracy when processing crimped or dirty banknotes [5]. Researchers worldwide have been motivated to develop reliable and efficient automatic counterfeit currency detectors. Introducing an automatic counterfeit currency detection technique would significantly enhance the country's financial security. Advancements in deep learning (DL) techniques coupled with machine learning algorithms have revolutionized the process of fake money detection by extracting valuable details from money images, like texture, color, shape, and geographic data. Deep neural networks are effective for various real-time applications, and through transfer learning, a large dataset is not necessary [6].
Instead, a pre-trained model on a large dataset can be fine-tuned with a smaller dataset, improving the model's accuracy and design. Data augmentation techniques, such as color analysis, expand the dataset used for currency recognition, improving the accuracy of counterfeit detection and overcoming the limitations of human perception and UV technology. The development of machine learning techniques, such as support vector machines (SVM), which can extract crucial features from banknotes to distinguish between genuine and fake notes. These algorithms can be implemented in various locations with high cash flow, such as banks, ATMs, vending machines, and malls, to reduce the market's influx of counterfeit currency [7].
Despite the rise of digital transactions, banknotes remain the primary means of trade; making currency counterfeit detection critical. Counterfeit currency poses a significant threat to global financial systems and economies. Counterfeit currency, produced without legal sanction, is considered fraud [1].
The Central Bank of Iraq, which supervises the dinar, was keen to introduce new security features to avoid duplication and thus increase confidence in the money. These features are intended to make it difficult for counterfeiting agencies to reproduce banknotes with recognizability by the public and financial institutions [1].
One of the inspiring security factors is watermarks, which when documents are placed under a light source show characters or logos of historical importance to Iraq. Security threads are usually metallic, inked into paper, and include fine printing or other engravings that cannot be easily duplicated. Some denominations contain ink that changes color at a different angle than the original color making it more difficult for a counterfeiter. The main technique in this regard is fine printing, which displays small writings on the edges of the banknote that are difficult to decipher with the naked eye[8].
Since contemporary Iraq is gradually recovering from the shadow of the crisis and beginning to work on the issue of its economic restoration, safety and confidence in the national currency will remain its strong foundation for economic growth and attracting investors and partners from all over the world to continue the development of the dinar. The comprehensive security measures correlate to the international security standards for banknotes to safeguard the Iraqi dinar and secure the financial environment of Iraq from the threats of counterfeiting [9].
The goals of this paper are threefold. First, it aims to build an advanced system utilizing cutting-edge technologies and methods to detect counterfeit Iraqi currencies with high accuracy. Second, it emphasizes the pivotal role of deep learning and machine learning techniques in enhancing Iraqi currency recognition systems, addressing the significant challenges posed by the evolution of counterfeiting methods. Finally, the research seeks to contribute to the development of a more secure and resilient financial ecosystem, capable of mitigating the risks and threats posed by counterfeit currency in Iraq.

2. RELATED WORKS

The counterfeit money site is the primary test for developing nations globally's financial institutions, where imaginative solutions to countermeasure counterfeit approaches need to be enhanced slowly. In recent times, researchers have considered the employment of deep learning computations in enhancing false recognition potential particularly by the convolutional neural networks (CNNs). Here, the author gives an overview of the work in this area of study, reviewing the many techniques employed, the outcomes of such assessments, their attributes, and the main limitations of current tests.
In 2018, Lee, et. al., [10] have developed an algorithm for the scanners to be designed with the deep learning ability to detect fake money on the bills. When it came to the production of the paper bills, they were able to counterfeit them with ease simply through using the colored laser printers to print the pictures that were produced by scanning the actual bills. In this study, the notable features include giving

the deep learning to the study, its ease in use by individuals with regular scanners in addition to its test with various printers.

In 2019, Laavanya and Vijayaraghavan [11] have used a deep convolutional neural network (CNN) for distinguishing fake currency. The transfer learning was applied by the researchers on the CNN established with the aid of the set of 2250 Indian rupee notes. The denomination-specific detection accuracies were as follows: When they asked to donate 50 rupees with 81 percent effectiveness, 200 rupees with 82 percent effectiveness, 500 rupees with 82 percent effectiveness, and 2000 rupees with 87 percent effectiveness.

In 2020, Pham, et al., [12]applied CNNs to differentiate real and counterfeit banknotes based on photographs taken with smartphones. In their experiments, they achieved an accuracy of as high as 99% to demonstrate how perfect it can be to apply photos that were taken with a smartphone in natural light. They include the popular handheld Smart-phone technology and enhanced detection capacity as among the key strengths of this approach.

In 2020, Dorstewani, et al., [13]employed a newly-developed Random Forest algorithm coupled with a Decision Tree classifier to advance fake currency categorization classification precision. The results show that the accuracy of the Random Forest Algorithm was higher than the Decision Tree Algorithm with the accuracy of 80.5%.

In 2021, Pachón, et al., [14] reviewed the inference speeds and realized performance of deep learning applied architectures including custom and transfer learning. It was extended by proposing a new model on an AlexNet-type sequential CNN and identified the extents of freezing points of CNN structures (sequential, residual, and Inception) for a given transfer learning technique. The network called ResNet18 fulfilled the greatest accuracy at a level of 100%.

In 2022, Diarra et al, [15] employed an automatic fake currency recognition system which would employ a peculiar CNN method in the identification of fake paper currency. For the same string, the CNN algorithm was used by the system to achieve an accuracy of 99 percent. Self-estimated ability and its correlation with achievement 46% with a loss of 0. 0033. Based on the result acquired from the experiment, the solution built on deep learning was found to outperform other shallow image-processing methods in the detection of fake currency notes.

In 2022, Sahil Das, et al., [16]have used some sub branches of image processing to investigate specific security characteristics and proposed a method for identifying counterfeit Afghan banknotes. The specific security features of fraudulent Afghan banknotes were also detected by the Random Forest system with 99% performance. This is one of the main assets of the study while dealing with fake products availability to the general public.

In 2023, Ashna & Momand, [17]aimed at designating a new concept of currency identification for the benefit of both the blind folks and the appropriating technology in the banking sector. First, they adopted deep learning approaches particularly Convolutional Neural Networks and image analysis. As consistent with this study, it was discovered that at different recognitive accuracy levels: Resnet50 at 83. 44%, VGG16 at 91. 6% and a CNN model developed for this study at 94.

In 2023, Smitha, et al., [18] which advanced a breakthrough support vector machine (SVM) technique for the identification of fake currency notes. It is a reliable tool with a recovery rate of approximately 99% of all identified errors. The picture data allowed the SVM to classify banknotes as genuine or fake with an accuracy of 55% The reject rate for the algorithm was 45%. That way, the ability of SVM was shown clearly just how good it was within the pattern categorization.

In 2024, Nasayreh et al., [19]designed a state-of-the-art deep CNN with an attention module. This approach would involve the use of leading features in the determination of the fakes while simultaneously eliminating those that were relatively irrelevant. Specifically, the dataset obtained from Kaggle contains different denominations of the Jordanian banknotes. By applying image processing techniques to boost brightness and create artificial images, our model achieved impressive results: An example of their work includes achieving 96% accuracy, 96%. 6% precision, 96. 4% recall rate and a 94. 5% F1 score. It maintained an 88% accuracy level on an Indian dataset and a 99% on the HIV/AIDS one whenever the model was tested on these datasets. 9 percent on both the DS1, DS2, and DS3 datasets. From this study, the proposed model effectiveness in identifying fake banknotes is evident hence the suggestion of better results when applied in the real world with worn out banknotes.

3. Dinar Security Features

Iraq has been using money since the Second World War, when it was a member of the India Monetary Region and the Indian Rupee was in use until 1932. Under Law No. 44 of 1931, Iraq formed the "Iraqi Currency Committee" in 1931. Later, the Iraqi National Bank—established by Laws Nos. 42 and 43 of 1947—took over currency issuance, replacing this committee [20]. The Iraqi National Bank was renamed

the Central Bank of Iraq in 1956 by Law No. 72. As per the provisions of Article 32 of the Bank's Law No. 56 of 2004, the exclusive jurisdiction to issue banknotes and coins for legal circulation in Iraq rests with the Central Bank of Iraq [21].
The Central Bank of Iraq is the sole authority to decide on the denominations, features, and patterns of its money, as stated in Article 33 of its legal charter. Additionally, it requires the Central Bank to supervise every facet of coin and banknote issuance, including distribution plans and the handling of damaged or withdrawn currency. The entire burden of guaranteeing that money, in the form of coins and banknotes, is always available in Iraq at all times and places rests with the Central Bank [22].
Two separate series define the history of Iraqi currency: the Republic symbol series, which ran until 1978, and the Royal series, which featured King Faisal's face and was in circulation until 1950. Up until 1990, the Soviet company Export less and the British company De La Rue printed the international series, also referred to as the Swiss series. Then, as a result of economic sanctions, the Dar Al-Nahreen printing house's currency printing was taken over by the Central Bank of Iraq [23].

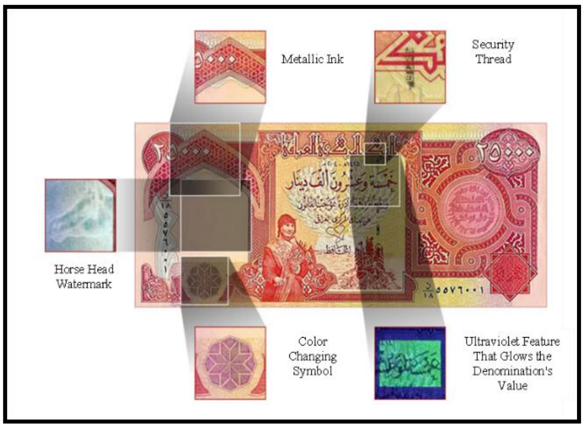

Figure 1. Iraqi Currency Security Features [Web]

All Iraqi banknotes, domestic and foreign, were taken out of circulation in the early 2003s because they lacked security measures and were made of commercial paper rather than security paper. They were replaced by brand-new, high-security banknotes from the Central Bank of Iraq, available in seven denominations. The Central Bank continuously improves these features and uses cutting-edge technology to detect counterfeit banknotes in order to combat counterfeiting and forgery [21].
In order to prevent counterfeiters and maintain the integrity and confidence of the country's monetary system, Iraqi currency is strengthened with a variety of advanced security features as shown in Figure (2-1). One of these precautions is the careful weaving of a specific security thread into the banknotes during the printing process. This thread, which is often where the pattern or writing increases or decreases, is the easiest to recognize as authentic and very difficult to forge in exact detail without advanced tools and know ledge[24].
Graphic elements on latest issues of Iraqi banknotes include a metallic ink which makes some of the notes shinning apart from the threads. This is because this metallic ink plays the dual role of making the money look better and at the same time making it most difficult for the counterfeits to make their antics work[25].
Also, in Iraq some added value; the value of the denomination is displayed on the banknotes when exposed to ultraviolet light owing to a UV square. The bright payment title can assist as a fast and extolled technique of verifying the cash, and includes this ostensibly unobtrusive security feature [25].
Extending the list of the security features, the emblem that indicates color change produces the overall security level of Iraqi banknotes even higher. This is a very useful and striking element which uses the effects of infrared and fluorescence inks that change the color depending on the lighting or position of the writing. The ends of the aforementioned optimal banknotes include qualitatively perfecting not only the look of banknotes but also making counterfeit operations challenging with the help of introducing dynamic patterns into the design of the banknotes[25].
Every Iraqi banknote also has their own watermark too, mostly the image of a horse head or other important image of the nation. This is an inscription typically inserted into the paper at the time it is manufactured or produced, and appears more clearly in the light. This rather slight but still easily noticeable additional detail contributes to the enhancement of the Iraq's banknotes security system by

only one element. This carefully integrated security features therefore put a formidable layer of protection against counterfeiting of the Iraqi banknotes thus ensuring that the future of its monetary system is secure and dependable [26].

4. METHODOLOGY

Model Block Diagram consists of a basic structure with sets of components having functional relationships that are easy to understand and analyze in its simplest form.
The detailed process of developing and deploying a machine learning model for the detection of fraudulent banknotes is captured in the Model in Figure (2). First, there is a brief introduction to the dataset and suitable emphasis placed on these models' application in financial safety as well as the nature of the binary classification task. The next section discusses different deep learning models that are as follows: Convolutional Neural Networks or CNN namely VGG16, MobileNetV2, and InceptionV3 of which each is developed to apply pre-trained architectures for purposes of feature extraction and classification.

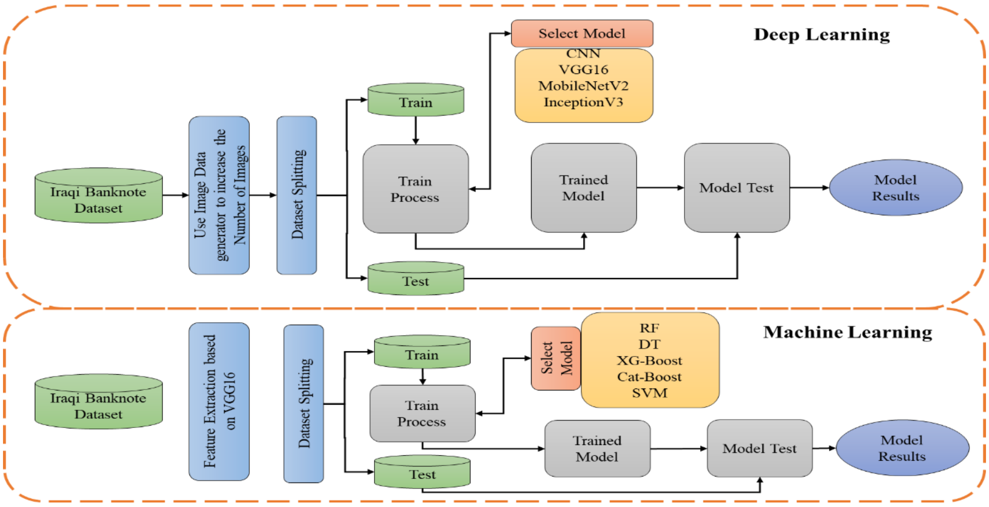

Figure 2. Model Block Diagram

The article also provides an explanation of the feature extraction process using VGG16, including training and testing datasets, preprocessing picture data, and feature extraction from transfer learning. It also includes features related to the use of machine learning algorithms that are configured with specific parameters depending on the task of classification applied to the given material, namely Random Forest, Decision Tree Classifier, XGBoost, CatBoost, SVM.

4.1 Dataset Description

The set-out data, depicted in the Table (1), also indicates that banknotes are categorized into real and fake banknotes. The feature vector and labels used in training is 1087 actual banknote and 558 false banknotes. Testing set contains 272 banknotes, out of which 140 were originals, and 132 banknotes were identified as counterfeit.
Indeed, in this case, we have a binomial classification and, therefore, the goal is to train a model that will be able to determine the genuine currency from the sham.
These models are essential to enforcing financial institutions and law enforcement organizations to counterfeiting. Authors might build models that function to identify features of actual cash money through the use of computer derived methods and strategies.
This will go a long way in preventing counterfeiting of banknotes. So, for the goal of enhancing security inside banking and financial organizations ultimately, this dataset comprises an essential foundation when establishing and examining these types of models.

Table 1. Dataset Size

Train	**Real**	**Fake**
1087	558	529
Test	**Real**	**Fake**
272	140	132

4.2 Dataset Augmentation

Through specification of implemented model and item models, these configurations ensure impartiality and sustainability in the training and valediction of every model. Table (3-2) below, outlines these parameters.

Table 2. Machine Learning Training Parameters

Model	Parameters			
Random Forest	No. of Tree	100	max_depth	4
Decision Tree	max_depth		5	
XG-Boost	max_depth		5	
Cat-Boost	max_depth		5	Learning Rate	0.01
SVM	Kernal		Linear	

4.3 Deep and Transfer Learning Models

Convolutional Neural Network Implementation

Figure (3) describe a model of a Convolutional neural network (CNN), a deep learning architecture most often used in image classification task. It consists of multiple layers intended for processing and feature extraction from input images.

First, learnable filters are applied for extracting part of input pictures through a convolution with convolutional layers (Conv2D). The initial Conv2D layer performs feature extraction from RGB images of size 64 x 64 pixels, employing 32 filters of differing sizes.

These filters propose a number of values from the input photos, such as texture, patterns, and edges. Specifically, Rectified Linear Units (ReLUs) brought non-lineariy to the model by setting negative pixel values to zero.

Max Pooling Layers (MaxPooling2D) are added after the Conv2D layers in order to minimize spatial dimensions and manage overfitting. Using the maximum value from each region and down sampling the data, max pooling works on small sections of the feature maps. This model reduces the feature map dimensions by performing max-pooling with a pool size of (2, 2).

To convert the multi-dimensional feature maps into a one-dimensional vector, a flatten layer is added after the convolutional and max-pooling layers. Feeding the data into Dense Layers (completely connected layers), the next parts of the model, requires this step.

To acquire high-level representations of the features that the convolutional layers extracted, two Dense Layers are incorporated. ReLU activation is used in the first dense layer, which has 128 units and makes it easier to identify complicated patterns in the data.

With a sigmoid activation function, the single unit that makes up the second dense layer. This last layer, which outputs the likelihood that the input image belongs to the positive class (class 1), is commonly used in binary classification problems.

All things considered, this CNN architecture successfully extracts hierarchical features from input photos, producing a model that can correctly predict results in image classification tasks. Convolutional and dense layers work together to teach the model how to identify patterns and use the retrieved features to inform decisions.

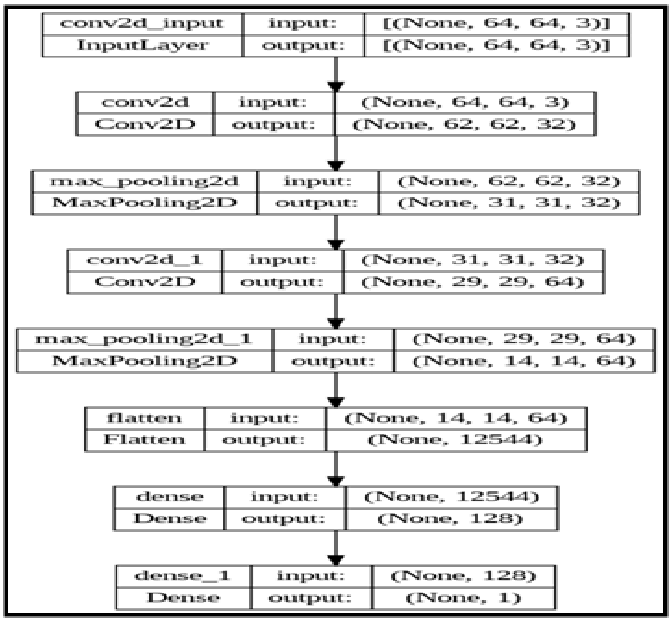

Figure 3. Convolutional Neural Network Design

VGG16 Model Implantation

The presented model in Figure (4) employs a transfer learning methodology, making use of the VGG16 architecture that has been pre-trained on the ImageNet dataset. The 16-layer VGG16 convolutional neural network, which is mostly made up of pooling and convolutional layers, is renowned for its simplicity and depth. We may use the VGG16 model as a feature extractor by setting {include_top=False}, which excludes the fully linked layers at the top of the model. The input shape is defined as (224, 224, 3), which complies with the VGG16 model's input size.

A Sequential model is built on top of the VGG16 base, with the first step being the Flatten layer, which converts the multi-dimensional feature maps into a one-dimensional vector. The input for later layers is this representation that has been flattened. In order to learn high-level features from the recovered VGG16 features, a Dense layer with 128 units and ReLU activation is added after the Flatten layer. After that, a Dropout layer is added with a dropout rate of 0.5 to promote robustness and generalization by randomly deactivating neurons during training and prevent overfitting.

The output layer for binary classification tasks is a Dense layer with a single unit and sigmoid activation that is appended at the end. Its function is to estimate the likelihood that the input will belong to the positive class.

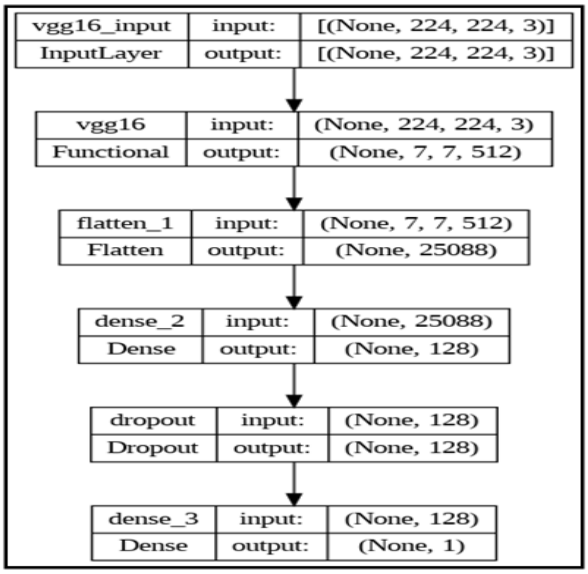

Figure 4. VGG16 Modified Model

MobileNetV2 Model Implantation

As previously illustrated in Figure (5), the model implemented in this study involves the transfer learning strategy for the MobileNetV2, a convolutional neural network that is small and designed for the embedded and mobile vision application. Data from the ImageNet model are then transferred to the MobileNetV2 model, where include_top=False is set to omit the fully connected layer. With this setting, MobileNetV2 becomes an efficient feature extractor that can extract salient features of input images.

They are set to not trainable by setting 'layer. trainable = False' so as to prevent the pre-trained layers in the underlying MobileNetV2 model to be modified during the training session; and probably hindering the learning of important features. It ensures that the task-specific data should not be used for anything but for training the custom classifier layers that are added on top.

The custom classifier is built using Several models such as the Sequential model. Feature vectors are one dimensional and acquired by reconstructing the MobileNetV2 base model output layer. To get representations of the contextually captured features, one more layer with 128 thick and ReLU is incorporated. To descent the risk of overfitting, dropout regularization of rate 0. 5, using a random strategy to deactivate neurons during training.

The output layer is then finished with a dense layer consisting of a single unit and a sigmoid activation function. This layer is suitable for binary classification tasks, where it estimates the likelihood of the input belonging to the positive class.

All things considered; this model makes use of MobileNetV2's potent feature extraction capabilities to tailor the classifier to certain classification tasks. The model can function effectively with little training data by fine-tuning only the recently added layers, which makes it suitable for a variety of picture classification applications.

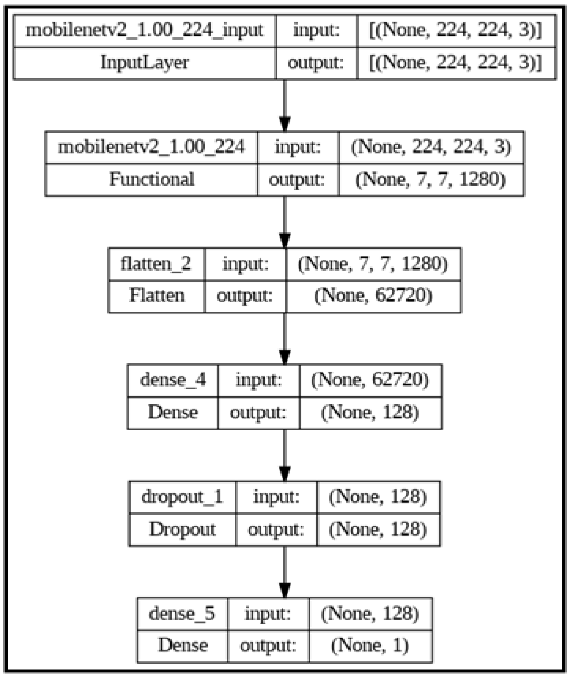

Figure 5. MobileNetV2 Modified Model

InceptionV3 Model Implantation

The model shown in Figure (6) uses a deep convolutional neural network called InceptionV3, which is optimized for image classification tasks. It is a transfer learning method. The fully connected layers at the top are excluded by setting `include_top=False}, and the InceptionV3 model is initialized with pre-trained weights from the ImageNet dataset. By using this technique, the InceptionV3 model may extract features from input photos and function as a feature extractor.

The frozen InceptionV3 base is then used as the foundation for a bespoke classifier. After being flattened, the InceptionV3 model's output is fed into a dense layer with 128 units and ReLU activation to produce a one-dimensional feature vector. The retrieved features are mapped by this dense layer to higher-level representations appropriate for the current classification task. After the dense layer, a dropout layer with a dropout rate of 0.5 is added, randomly deactivating neurons during training to prevent overfitting. Lastly, the output layer consists of a dense layer with a single unit and sigmoid activation. This layer is

appropriate for binary classification tasks, where it forecasts the likelihood that the input will belong to the positive class.
This model design changes the classifier in dependence with certain classification tasks but still uses the powerful feature extraction of the InceptionV3 model. The model can operate to its optimum with a minimal training data set and detail only the latest layers for fine-tuning, and thus the model is ideal for many picture classification applications.

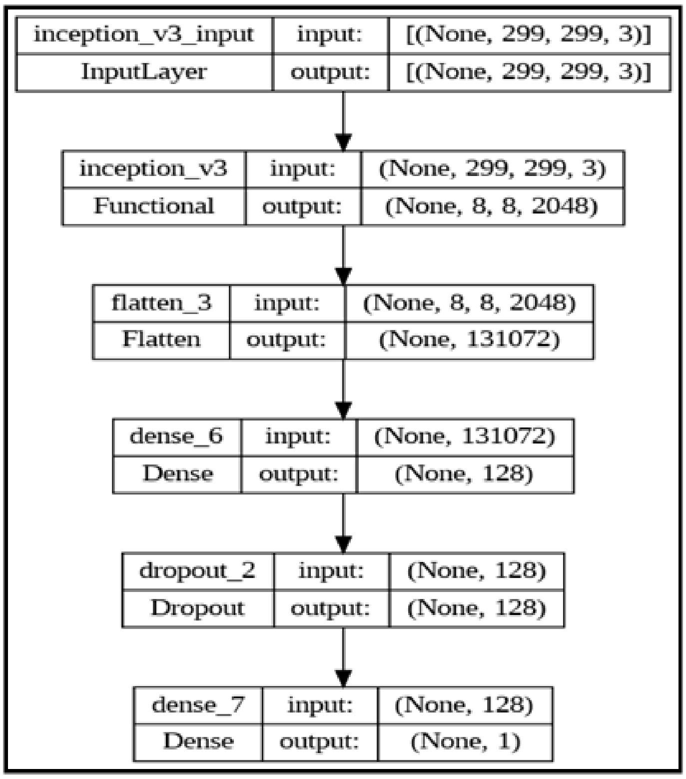

Figure 6. InceptionV3 Modified Model

DenseNet 201 Model Implantation
In the model of Figure (7), a deep" convolutional neural network known as DenseNet201 for image classification is implemented. This is a method of transfer learning where features are learned from one task and then shared with another task. The denseNet201 classifier is initially trained on a dataset called ImageNet and the final layers of the network are removed using the include_top parameter set to False. This method makes it easier to function DenseNet201 model as a feature extractor through allowing it extracting features from input pictures.
A new DenseNet201 base is then made as a frozen model and a new classifier then developed on top of the frozen model. After flattening the feature map from the DenseNet201 model, the feature map is passed into a dense layer with 128 units activated with ReLU activation. This dense layer turns the obtained characteristics into formats more convenient for the current classification type. To mitigate this, we employed a dropout layer for regularizing the neurons and set the dropout rate at 0. 5 is added after the dense layer To adhere to the recommended Averaged Precision of 5, it is added after the dense layer. This layer has the capability of making neurons inactive during training in a random manner. Finally, there is the sigmoid activation function for the last layer and the dense layer with a output of one neuron. When applied to the binary classification problems, this layer estimates the chances that some input data has to belong to the positive class.
This model design makes use of feature extraction obtained from DenseNet201 and provides specialized classification capabilities to the classifier. Of particular interest, by fine-tuning only, the recently added layers the model may run effectively with little amount of training data; thus suitable for a vast of photo categorization solutions.

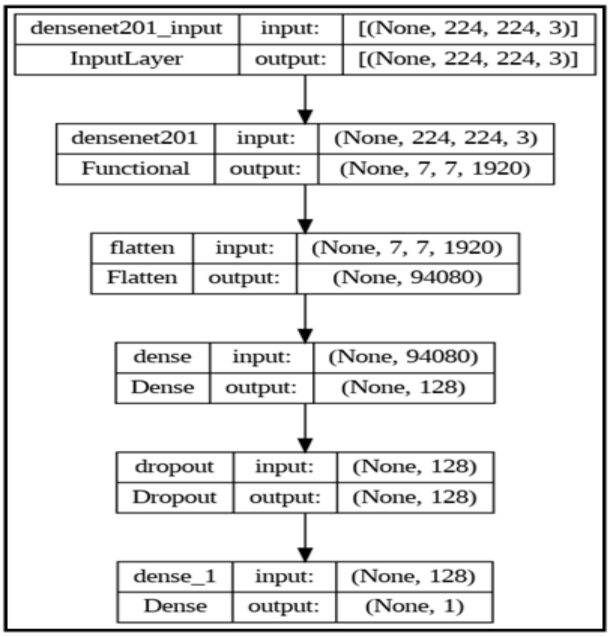

Figure 7. DesnseNet 201 Modified Model

4.4 Hardware Design

Several components used: We used some components that include Raspberry Pi 5, Raspberry Pi Camera Module, Servo motor, LCD screen, Breadboard, Jumper wires, power supply, and Pre-trained Machine Learning model. First of all, place the camera module on the Raspberry Pi with the appropriate port and take care to make the ribbon cable safely. Next, the servo motor should be connected for its signal wire is connected to GPIO pin (for example GPIO 18), power wire is connected to the 5V, and ground wire is connected to GND pin of the Raspberry Pi. As for the I2C LCD it is simple; solder SDA and SCL pins the SDA (GPIO 2) and SCL (GPIO 3) of the Raspberry and connect VCC n GND to the 5V and GND pins.

After the basic connections in the hardware have been done, proceed to install the requisite software by invoking appropriate libraries like RPi. GPIO for GPIO access, smbus2 for Inter Integrated Circuit control, OpenCV for processing pictures, TensorFlow or any other machine learning library for managing the model. Along with using PWM, to write a python script to control the servo motor and capture images with camera using OpenCV and test the images with the trained model. Last, code to power up the LCD screen and regulating its operations to display the results.

In the main program, first of all, control the servo motor to position the paper coin, then use the camera to capture an image, subsequently, using the pre-trained saved machine learning model to test the image, and lastly, display the result on the LCD screen. It is very convenient for the user to set up the motion of an object, the taking of the picture, the application of a machine learning algorithm to the resulting image, and the representation of the output, all in one neat and tidy package.

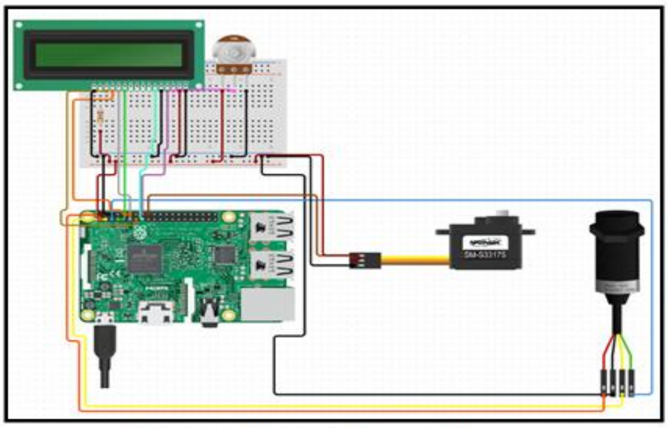

Figure 8. Hardware Circuit Design

4.5Counter Box Design

The box designed for the counter in Figure (9) device consists of a hanging box with three openings, two opposites to each other for the currency to enter and exit, and another above to display the test result on the screen, while the box contains a circular track in the form of a ring controlled by a motor to pass the banknote.

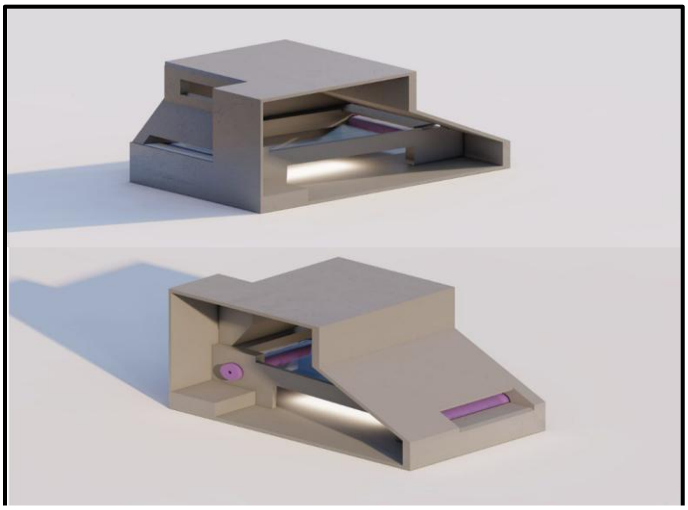

Figure 9. Designed Device Box

5. RESULTS

5.1 Deep Learning Results Discussion

When training multiple models on the examinee data the models include, CNN, VGG16, MobileNet V2, Inception V3, and DenseNet201 exhibit varying levels of effectiveness in accuracy and loss as seen on the outcomes of training and validation datasets. It provided near 100% training accuracy, a condition that saw this work develope 91% The confusion matrix values are TP= 989, FP= 1, FN = 11, TN =944. The size of the pre-trained model was reduced to 26%, and DenseNet201 won ahead of the other models in terms of accuracy. In the same vein, DenseNet201 exhibited the minimum loss figures of 0. 011 for training and 0. 0181 for validation, meaning it delivered low loss with little signs of overfitting.

Other than DenseNet201 Inception V3 also performed well with a greater focus on the validation accuracy 99: 26% albeit to a higher loss. Despite their loss values being slightly higher than DenseNet201, the VGG16, MobileNet V2 along with CNN also gave good accuracy.

They also suggest that these designs, while being successful, may not transfer as readily from one context to another. Typically, this classification assignment could suggest that DenseNet201 seems to be one of the most accurate and the least loss-prone models out there as it is moderately positioned in between. It is also important to analyze the Deep learning results as shown in Table (3.).

Table 3. Deep Learning Results

Model	Accuracy			Loss		
	Train	Validation	Test	Train	Validation	Test
CNN	0.98	0.99	0.99	0.04	0.03	0.03
VGG 16	0.99	0.98	0.98	0.02	0.03	0.03
Mobile Net V2	0.98	0.99	0.99	0.02	0.03	0.03
Inception V3	0.97	0.99	0.99	0.05	0.02	0.02
DenseNet 201	0.99	0.99	0.99	0.01	0.01	0.01

Machine Learning Results Discussion

Exploring mathematical machine learning models for real and forged banknotes identification, authors show the efficiency of specific algorithms. A paramount performance since Random Forest shows an accuracy, precision, recall, and F1-score of, respectively, 96%. Its Decision Tree Classifier shows also slightly lower accuracy comparing to Random Forest what is 83% in all keys.

XGBoost ranks first with the highest efficiency of 97% for the accuracy together with the precision, recall, and F1-score rates in classification problems. CatBoost is a clear winner achieving the highest scores of 98% on all of the four points emphasizing that the algorithm is better than others.
Likewise, Support Vector Machine shows great performance up to the mark with CatBoost with accuracy of 98% along with the precursor of 0. 98, recall value of 0. 98 and F1-score of 0. 980. Thus, when it comes to performance based on accuracy and reliability CatBoost, SVM, and XGboost are declared the best algorithms for classification of banknote, the Random Forest also shows a good result.

Table 4. Machine Learning Evaluation Metric

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.96	0.96	0.96	0.96
Decision Tree Classifier	0.83	0.83	0.83	0.83
XG-Boost	0.97	0.97	0.97	0.97
Cat-Boost	0.98	0.98	0.98	0.98
Support Vector Machine	0.98	0.98	0.98	0.98

5. CONCLUSIONS

As presented in this thesis, the use of advanced machine learning and deep learning approaches improves the classifier's performance in identifying fake banknotes and is much more effective than using conventional approaches. To enhance the security of the Iraqi currency from counterfeiting the following have been incorporated; Horse head watermark, Security thread, Metallic ink. These features offer the multiple layers of protection and that is why they are very challenging to imitate using any of the counterfeiting techniques.
As it is clear, the banknotes have incorporated strong features that would discourage the forgery of money and at the same time enhance the identification of the fake money by the public. Such characteristics as colored symbols that change color and UV marks that become visible under certain lighting conditions help to quickly and confidently distinguish fake banknotes. It is almost impossible to replicate some of the reflective and security features of the current notes such as metallic ink and security threads. These characteristics do not only make the currency more secure but also make it easier to distinguish genuine banknotes.
For instance, the use of horse head watermark is a good security feature that can be adopted. When exposed to a light source, this feature is apparent, and thus, it is an effective way of proving the authenticity of the product since it is almost impossible to create an exact replica of the same. Another security measure is the ultraviolet one that shows the numeral value of the money under the ultraviolet light. This makes it possible to quickly and non-contacting check the banknotes, which will help quickly determine the authenticity of the money.
Despite the fact that the current security mechanisms are highly effective, there is a need to constantly review and improve on these aspects of the system. The fight against counterfeiting does not stop and this means that the security technology used has to be updated so that the currency is protected. While it comes to counterfeit detection, deep learning using Convolutional Neural Networks (CNNs) has been found to be more than 90% accurate. Other algorithms such as CatBoost and Support Vector Classifier (SVC) are also well known for their ability in the identification of counterfeit currency notes with high accuracy.
Since counterfeiting techniques are constantly changing their ways to fool the detection systems, so does machine learning and deep learning techniques. This is the reason why the continuous development of these monetary systems is crucial in the preservation of the world's financial systems. As it can be seen, financial institutions as well as law enforcement agencies can enhance their efficiency of detecting counterfeit currencies by employing these enhanced detection technologies. This will assist in reducing cases of financial losses and ensure stability of the national economies.
When used appropriately, these technologies serve as a protection of the financial system by maintaining the public's trust in the currency and credit. This is especially important to global organizations that are responsible for the wellbeing of the world's economy and counteracting the impacts of circulating fake money.

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