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Counterfeit (Fake) Currency Detection using Mobilenet and Resnet Models

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***Abstract*—The global economy is seriously threatened by the growing problem of counterfeit currency circulation which erodes confidence in monetary systems and causes financial instability. Real-time fake currency detection is a difficult challenge that requires creative solutions especially given the variety of counterfeit currency notes. Physical examination is a major component of traditional counterfeit detection techniques but it can be laborious, error-prone and non-scalable. In order to solve this issue, this work builds an automated system for detecting counterfeit currencies using MobileNetV2 and ResNet designs and sophisticated deep learning techniques. To increase the robustness of the model the dataset which was gathered from several internet sources is enhanced using a variety of data augmentation approaches. The main objective of the model is to correctly identify genuine or counterfeit money notes. When identifying real or fake currencies using CNN-based structures MobileNetV2 obtained an astonishing 99.03% accuracy whereas ResNet achieved 74.03%. Additionally, the system may identify the denomination of notes of currency such as 10, 20, 50, 100, 200, 500 and non-currency Images. Using Image Augmentation and preprocessing methods for improved model performance allows for this. Furthermore, the system makes use of streamlit as the real-time currency detection user interface providing a user-friendly and easily accessible platform that enables users to instantaneously verify the legitimacy of currency notes. The method is an efficient way to detect counterfeit currency because of its 94% overall accuracy in identifying both forged notes and their corresponding denominations.**

***Index Terms*—Counterfeit Detection, MobileNetV2, ResNet-50, Currency Classification, Image Processing and Streamlit UI.**

I. INTRODUCTION

The spread of counterfeit money has become a major worldwide problem that threatens the stability of economies and causes enormous financial losses [1]. The ability to create counterfeit notes has advanced with technology presenting a significant problem for businesses, financial institutions and law enforcement. In addition to causing immediate financial losses counterfeit money also destroys the economy and makes people feel nervous. Conventional techniques for identifying counterfeit currency like holograms, watermarks, manual inspection and ultraviolet (UV) radiation scanning, are frequently laborious, ineffective and prone to human mistake. In order to detect fake currency reliably, quickly and on a large-scale novel and automated technologies are therefore desperately needed. Advances in computer vision and deep learning have created new opportunities for automated counterfeit detection systems. It is now feasible to develop intelligent systems that can precisely distinguish between genuine and counterfeit currency by using convolutional neural networks or CNNs and cutting-edge models such as MobileNetV2 and ResNet. These models can analyze complex aspects of currency notes that are hard for the human eye to pick up on, like consistency, patterns and other distinguishing markings [2].

Over 6.6 million counterfeit notes were found in 2020 alone, according to the Reserve Bank of India (RBI) which reports that the amount of counterfeit cash in circulation has been rising rapidly. Higher amounts like ₹500 and ₹2000 that are more often used in everyday transactions make up nearly all of these fake notes [3]. These counterfeit notes undermine the efficacy of monetary policy and add to the issue of black money. As of 2020 counterfeit cash accounted for about 0.025% of all Indian currency in circulation mostly in the ₹500 and ₹2000 grades. More sophisticated and effective detection techniques are now required to stop the spread of counterfeit money as a result of this worrying development. Furthermore, organized crime, the funding of terrorism and other illicit activities have been connected to the circulation

of counterfeit cash in India underscoring the need of early detection of counterfeit notes. The issue of counterfeit money is equally serious on a global scale.
The International Monetary Fund (IMF) estimates that the total amount of counterfeit currency in circulation globally was around $1.1 billion in 2018 [4]. With counterfeit notes mostly in high-value denominations like the $100 bill in the US and the €500 bill in the Eurozone, the US, Europe and a number of Asian nations are most affected. Traditional detection systems are finding it more and more difficult to keep up with the development of advanced printing technologies. Adoption of cutting-edge technologies such as AI-powered counterfeit detection systems is thought to be a crucial way to deal with this expanding issue. To increase security and operational efficiency, banks and other financial institutions in numerous nations are currently investigating the use of artificial intelligence (AI) and machine learning (ML) algorithms to automate the detection of counterfeit cash [5]. The research described in this article supports this international effort by offering a strong framework for deep learning-based counterfeit cash identification.

Objectives:

- Developing a robot that uses deep learning models like MobileNetV2 and ResNet to identify fake currency.
- Detecting fake currencies and classify denominations with precision in real time.
- Use picture preprocessing and data augmentation strategies to improve the model's performance.
- Use streamlit to create a simple user interface for quick and easy real-time currency verification.
- Compare and evaluate the effectiveness of the MobileNetV2 and ResNet systems for identifying denominations and detecting fake banknotes.

II. LITERATURE SUREVY

The application of deep learning and machine learning methods for the detection of counterfeit currency has been the subject of several studies in recent years with encouraging outcomes. Conventional techniques mostly depended on physical characteristics like watermarks, UV light scanning and analysis of texture but these techniques frequently failed to identify fake notes particularly as fraudsters became more skilled. Convolutional neural networks also known as CNNs were chosen by a number of researchers due to their capacity to automatically identify complex patterns in images as technology for deep learning gained popularity [6]. According to studies, CNNs can be very good at identifying complex aspects of money notes like minute patterns and texture details that set authentic notes apart from fake ones. In one noteworthy work a hybrid model that included CNN algorithms and support vector machines (SVM) was used to detect counterfeit cash and it achieved above 95% accuracy.

Bhatia et al. investigates the use of conventional techniques such as color, width and serial numbers to detect counterfeit cash. It suggests a technique for identifying counterfeit banknotes that makes use of image processing and K-Nearest Neighbors [7]. This method is appropriate for tasks involving computer vision since it detects and identifies counterfeit cash with 99.9% accuracy. High statistical and mathematical techniques are used to build the banknote authentication dataset. Bandu et al. examined an international problem impacting economies and security is the growing creation of counterfeit currency especially in India. A Convolutional Neural Network (CNN) a type of artificial intelligence and machine learning is used in a proposed false note detection system to identify distinct security aspects in banknotes [8]. For all six security elements the system's remarkable accuracy of 91.66% was attained in the Indian currencies of Rs. 500, Rs. 200 and Rs. 100. Chandrappa et al. introduces a novel approach that uses machine learning techniques to detect fake Indian notes depending on their photographs. Local key locations on each image are defined, and differences between images are represented using a vector space. For the purpose of eliminating mismatched vital locations a post-processing method is recommended. Since there aren't many counterfeit notes in use one-class training is used to identify fake currency.

Furthermore, the ability to detect counterfeit goods has been significantly improved by developments in deep learning models especially in designs such ResNet, MobileNet and InceptionV3. Because of their reputation for resilience and capacity to manage huge, intricate datasets these models are ideal for real-time currency verification applications. The MobileNetV2 model's lightweight architecture and effective feature extraction capabilities allowed for high accuracy rates (over 98%) for fake detection in one investigation. Similar deep learning methods have been used in research to identify particular money note denominations in addition to detecting fake banknotes. Researchers were capable of to identify the value of the note in addition to determining if it was real or counterfeit by experimenting with models with labelled datasets that included pictures of various cash denominations [10]. For real-world applications like Machines and cash-handling systems wherein both aspects are essential for smooth operations this dual functionality of understanding validity and denomination is essential.

Limitations of Existing System:

- Numerous earlier studies relied on limited datasets which had an impact on the models scalability and applicability.
- Manual involvement was necessary for traditional procedures which made them difficult and susceptible to human mistake.
- The computational cost of certain deep learning models limited their deployment on devices with limited resources and their real-time applicability.
- Prior studies models frequently had trouble processing damaged or low-quality cash images which reduced their accuracy.
- The robustness of many methods was impacted by their failure to account for the identification of counterfeit notes under various lighting and environmental circumstances.

III. DATA COLLECTION & PREPROCESSING

To guarantee a complete and representative dataset the data selection for this study entails compiling a varied collection of currency note photos from multiple internet sources. To help the model distinguish between real and counterfeit notes, the dataset contains high-resolution photos of various cash amounts both real and counterfeit. To replicate real-world settings and increase the detection system's resilience the collection also contains pictures of money notes shot in a variety of lighting, angle, and backdrop contexts. Each image of a currency note is labelled with the appropriate value for the currency denomination grouping task including ₹10, ₹20, ₹50, ₹100, ₹200, ₹500 and non-currency images (as shown in Fig.1). By including such a wide range of data, the algorithm used for deep learning is guaranteed to correctly detect and identify the cash notes denomination as well as their legitimacy. To solve the problem of insufficient data and improve the model's capacity for generalization, data augmentation is the first step in the preprocessing stage after the dataset is gathered [11]. Rotation, rotating, enlargement and cropping are some of the techniques used to artificially expand the data base and provide the model a wider variety of instances to work with. This makes the model more resistant to small adjustments to the images such as changes in scaling, rotation and orientation [12].

Fig.1 Collection of Currencies of Various Class

In addition to broadening the dataset's diversity image augmentation strengthens the model's capacity to real-world problems like minute differences in the way banknotes are photographed. By avoiding overfitting and ensuring that the model used for deep learning learns more generic features this procedure enhances the network's capacity to handle unknown data [13]. All of the currency note photos are scaled to a fixed height as part of the subsequent preprocessing procedure. This is important since CNNs and other deep learning models need uniform input image sizes. The model can handle the input and execute calculations more effectively and without encountering problems with inconsistent image dimensions if the photos are resized to a consistent shape. Additionally, by lowering the computational load this step improves the model's efficiency during both inference and training. In order to ensure that sufficient detail is preserved while reducing processor time and memory needs, the resizing procedure usually entails altering the photos to a resolution that strikes a compromise between image quality and computing efficiency.

Normalization is used to scale the image pixel values after resizing [14]. One important preprocessing method for accelerating the model's rate of convergence during training is normalization. Although the image pixel values span from 0 to 255 it is common practice to scale them to a smaller range, usually between 0 and 1 in order to improve the performance of deep learning models. The pixel values are divided by 255 to achieve this. The model can learn more effectively by normalizing the images because it avoids problems brought on by different input scales which can prevent training and result in less ideal performance. This guarantees that during the training process the model handles every input feature equally which promotes quicker convergence. Normalization is simply one aspect of picture preprocessing other methods include denoising and contrast adjustment. By highlighting the finer details of currency notes contrast enhancement makes it simpler for the representation to discern between authentic and counterfeit notes. Noise-reducing methods [15] such as Gaussian blur or median filtering are employed to remove noise from the images which might otherwise render it more challenging for the algorithm to identify significant features.

To separate the dataset into testing, validation and training sets data splitting is the last step. Usually training uses 70–80% of the data, validation uses 10-15% and testing uses the remaining 10-15%. While the set for validation is used to adjust its hyperparameters and evaluate its performance during training the training set of parameters is used to train the model [16]. To ascertain the extent to which the model applies to new data the set of tests is set aside for the last assessment. This makes it possible to reliably evaluate the model's performance on brand-new, unseen money notes and prevent it from overfitting to the initial training set. To avoid bias and overfitting proper data dividing is necessary enabling a fair assessment of the model's performance in real-world scenarios.

IV. PRINCIPLES AND METHODS

Modern deep learning models such as MobileNetV2 and ResNet are used in the suggested fake currency detection methodology to achieve outstanding precision in identifying both real and fake cash notes and dividing their values. Gathering a varied dataset containing pictures of genuine and fake banknotes in different denominations is the first stage in the process. Extensive data augmentation techniques including rotation, flipping, enlargement and cropping are used to improve this dataset. These techniques artificially enlarge the dataset and provide the model more diverse samples to train on. After that the photos undergo preprocessing which includes denoising to reduce noise and enhance image quality normalization to scale the values of pixels and scaling to a consistent dimension. In order to produce reliable and accurate results these procedures guarantee that the models used for deep learning receive high-quality and consistent inputs. Training two main designs MobileNetV2 and ResNet to gather relevant information from the photos and classify them according to denomination and validity (genuine or fraudulent) forms the basis of the process.

To guarantee that the system can carry out immediate identification on portable and devices with limited resources without losing accuracy, MobileNetV2 which is known for its compact architecture was selected. It is very effective for deployment in real-world applications since it makes use of depth-wise recoverable convolutions which significantly decrease the parameters. The issue of vanishing gradients is avoided by ResNet's deep residual learning design which makes it suitable for handling very deep networks. Convolutional and fully linked layers are used to train the models on the preprocessed pictures. The final output levels are made to forecast the particular denomination and classify the money notes as either true or fake. The capacity of the suggested methodology to deliver real-time detection supported by an intuitive interface created with streamlit is one of its primary features. Users can upload pictures of currency notes to the system and the model will evaluate the photographs in real time and determine if the note is genuine or fake. It will also indicate the denomination of the note.

A. Convolutional Neural Networks

In order to identify the complex characteristics of currency notes that set authentic ones apart from counterfeit ones, the Convolutional Neural Network (CNN) utilized in the effort to detect counterfeit currency is essential. Because CNNs can learn spatial feature hierarchies over numerous layers, they are very good at image recognition tasks. These networks are perfect for applications like currency note detection, where minute details are crucial because they are made to automatically identify patterns like edges, textures, and forms. Convolutional, pooling, dropout and fully interconnected layers are among the several layers that make up the CNN framework [17] used in this study (as shown in Fig.2). These layers cooperate to process and classify difficult visual data. The layer of convolution which is the CNN's initial layer is the fundamental layer for the extraction of features. A collection of filters, sometimes referred to as kernels are applied to the input image in this layer in order to identify different low-level characteristics including textures and edges. By taking the dots that are the result of the filter and the input image the convolution operation creates a feature map that draws attention to particular aspects of the image.

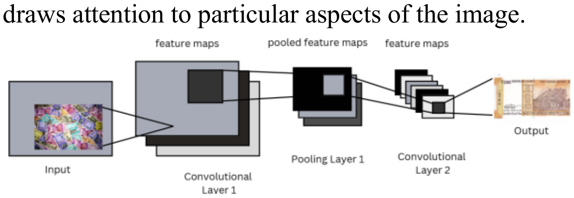

Fig.2 CNN Architecture

The function of activation which adds non-linearity to the network comes after the convolutional layer. This work uses the Rectified Linear Unit (ReLU) activation function [18] which keeps the positive numbers in the attribute map while replacing all of the negative ones with zero. This enhances the model's ability to learn and better capture intricate patterns. Because of its ease of usage and capacity to speed up convergence during training ReLU is frequently utilized in CNNs. The activation function is a crucial step in improving the information that is supplied through the network since it guarantees that the CNN may learn from the input information by highlighting some aspects and ignoring others. The pooling layer in the CNN, is in charge of down sampling the function maps that the convolutional layer has created. By reducing the geographic scope of the data pooling lets the network concentrate on the most crucial properties while lowering computational complexity. The greatest amount from each little area of the map of features is chosen in this project using max pooling.

B. MobileNetV2

For portable and embedded devices MobileNetV2 is a portable, effective deep learning model that strikes the ideal balance between accuracy and computing cost [19]. MobileNetV2 is used in this counterfeit cash detection system to distinguish between genuine and counterfeit currency notes and their denominations. This makes it perfect for use on devices with limited resources such smartphones or inexpensive hardware. Compared to conventional convolutional neural networks the model's depth-wise separable convolutions significantly cut down on both the number of variables and computational overhead. This renders MobileNetV2 a good option for jobs requiring real-time processing and high efficiency such identifying counterfeit currencies in daily life. MobileNetV2 is used in this research to process photos of cash notes and generate highly accurate predictions. MobileNetV2's usage of the inversion residual block architecture (as shown in Fig.3) is its primary innovation. This block structure maintains the network's capacity to learn intricate features while improving computational performance. The depthwise separated convolution, the straight-line obstacles and the quick connection are the three primary layers that make up each inverted residual block.

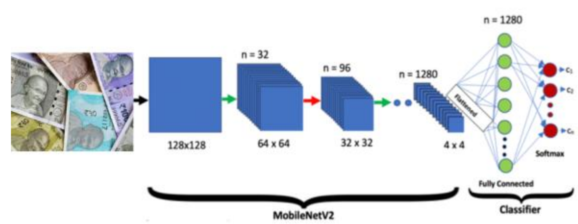

Fig.3 MobileNetV2 Architecture

The straight bottleneck is another essential element that enhances MobileNetV2's efficiency within the inversion residual block. A compact 1x1 convolution and an activation function for ReLU make up the linear bottleneck which shrinks the feature maps' spatial dimensions. The network can capture essential characteristics for currency detection thanks to this bottleneck architecture which also helps to keep computational costs down. The shortcut link the last stage in the inverted excess block reduces the possibility of disappearing gradients a frequent issue in deep networks, and enables the effective transfer of information between layers. The model will acquire deep abstract features thanks to this framework without being overly computationally costly. A deep neural network that can acquire hierarchical structures for the input photos is created by stacking these reversed residual blocks on top of one another in the MobileNetV2 architecture. The network learns increasingly abstract properties as the data moves through the layers beginning in the early layers with fundamental designs like edges, colors and moving on to more complex patterns in the deeper layers.

C. ResNet-50

One of the most popular architectures for a variety of image identification applications including the detection of counterfeit banknotes is the deep convolutional neural network, also known as model ResNet-50 [20]. The model's usage of residual knowledge through shortcut connections is referred to as "Residual Network" hence the name ResNet. In highly deep designs, these shortcut connections allow the network to learn more efficiently by avoiding one or more layers. The 50-layer ResNet-50 model is well-known for avoiding the vanishing gradient issue which is a frequent difficulty in deep network training (as shown in Fig.4). This skill is essential for intricate image identification tasks like detecting counterfeit currency, where it's necessary to capture the minute features in photos in order to differentiate between genuine and counterfeit notes. Residual blocks which enable the network to learn how to identify itself when required are the fundamental idea behind ResNet-50. Several layers of convolution with connection shortcuts that bypass one or more levels make up these leftover blocks. By adding a residual block's input straight to its output the shortcut connections enable the network to concentrate on understanding the residual mapping rather than the entire transformation.

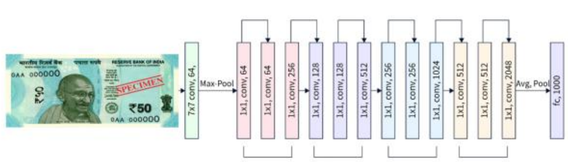

Fig.4 ResNet50 Architecture

The model takes advanced characteristics from the input photos by approving them through an array of layers of convolution, where each layer has responsibility for learning various elements of the images. The initial layers in ResNet-50 focus on basic characteristics like edges and textures while the subsequent layers acquire more abstract representations, like the fine details and structures that distinguish counterfeit currencies from authentic ones. ResNet-50 is essential to this counterfeit currency identification system because it processes images of bills in order to identify them as either genuine or fake. In order to address the degradation issue in deep networks ResNet-50 presents a fresh solution while utilizing a conventional convolutional neural network architecture. Because it is more difficult to maximize weights across all layers a network's performance tends to suffer as its depth grows. ResNet addresses this by using skip connections which allow the algorithm to learn residuals that is the variations between the identity function and the output. The usage of bottleneck layers inside the residual blocks is one of ResNet-50's distinctive features. Three convolutional layers usually make up a bottleneck layer: a 1x1 convolution for reducing dimensionality a convolution of 3x3 for extraction of features and an additional 1x1 convolution for feature map dimension expansion. Because it lowers the model's parameter count without compromising speed this bottleneck design is incredibly effective.

V. RESULTS

Three deep learning models CNN, MobileNetV2 and ResNet-50 are used to evaluate the fake currency detection system's outcomes. Plotting of several performance indicators including precision, recall, accuracy and loss curves is done to assess each model's efficacy. With a 95% accuracy rate a convolutional neural network (CNN) model which was created especially for money classification is a very dependable model for recognizing various monetary denominations (as shown in Fig.5). With a success rate of 99.03% the MobileNetV2 model surpassed the other models proving its effectiveness in accurately classifying both genuine and counterfeit money notes. Even though ResNet-50 is a strong deep learning architecture its accuracy was only 74.03%. This is mainly because of its deeper design, which might have needed more fine-tuning and bigger datasets to perform at its best.

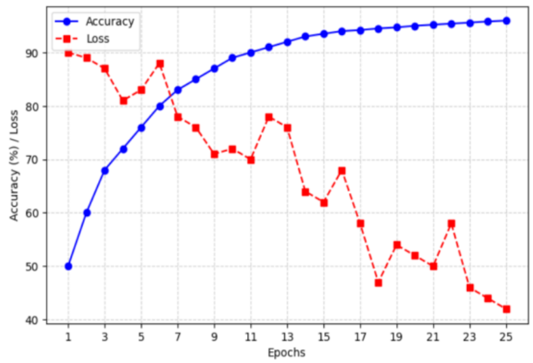

Fig.5 CNN Accuracy and Loss for Currency Classification

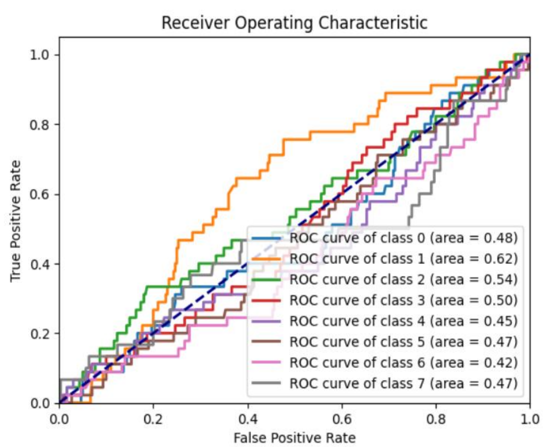

Fig.6 ROC Curve for CNN Model

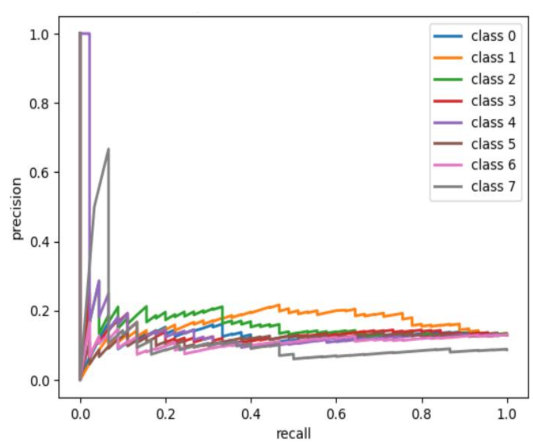

Fig.7 Precision, Recall Curve for CNN Model

These models' performance charts provide important information about how they learn. Indicating that the CNN model was properly trained and generalized for currency classification it displays learning curves that are steady with little oscillations (as shown in Fig.6&7). The smooth convergence of MobileNetV2's loss curve indicates that the model learnt from the data effectively and without overfitting. Throughout training, MobileNetV2's validation accuracy stayed constant at a high level demonstrating its resilience for real-time classification. Conversely, ResNet-50's loss curve showed more oscillations indicating that the model had trouble generalizing. Its deeper network structure which necessitates a larger dataset and adjusting hyperparameter to achieve optimal performance may be the cause of this. Using a streamlit graphical user interface (UI) the outcomes of the model training were incorporated into a real-time fake cash detection system. Users can input pictures of currency notes through the user interface (UI) and deep learning algorithms evaluate them to assess their authenticity. The model shows the likelihood scores for every prediction once a user submits a picture and determines if the note is authentic or fraudulent. Because of its exceptional accuracy the MobileNetV2 model was mostly employed in real-time detection settings guaranteeing accurate and speedy classification results.

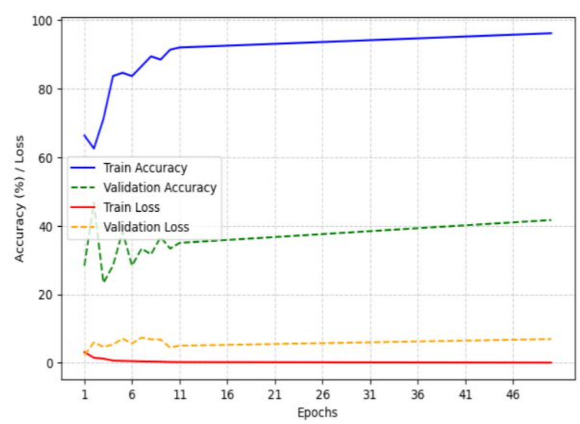

Fig.8 MobileNetV2 Epochs vs Evaluation Metrics

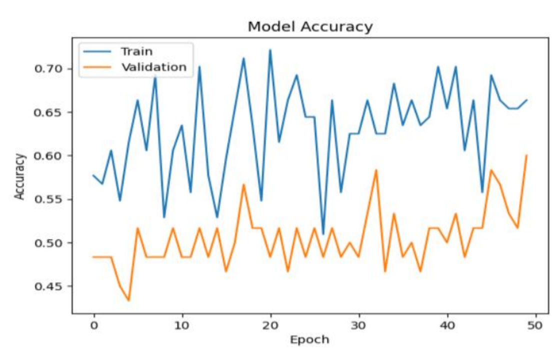

Fig.9 ResNet50 Accuracy, Loss vs Epochs

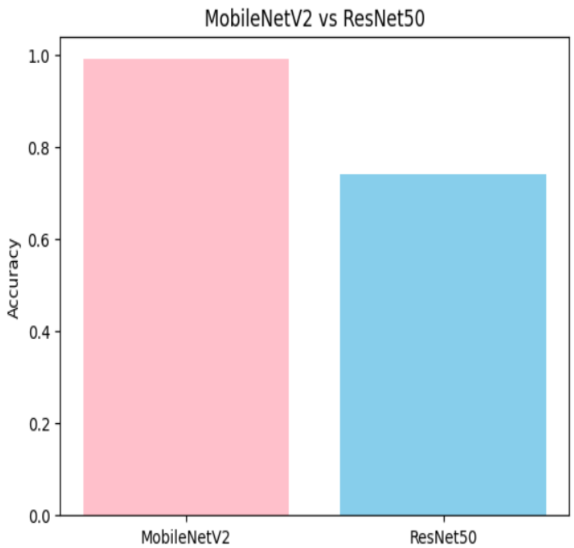

Fig.10 Comparison of MobileNetV2, ResNet50 Accuracy

The effectiveness of neural network models in counterfeit detecting is demonstrated by the real-time examination of money notes using the created detection system. Real and counterfeit cash notes were shown to the system in real-world testing settings in order to assess its accuracy and reaction time. Several denominations such as ₹10, ₹20, ₹50, ₹100, ₹200, ₹500 and non-currency images, were effectively categorized by the system which confidently distinguished between genuine and fake notes. With a 99.03% classification accuracy for counterfeit notes MobileNetV2 continuously produced accurate predictions (as shown in Fig.8). CNN was a trustworthy substitute for currency classification coming in second with a 95% accuracy rate. ResNet-50 was still effective to detect important counterfeit traits albeit with sporadic misclassifications (as shown in Fig.9) while having a somewhat lower accuracy rate of 74.03% (as shown in Fig.10). The first phase in the multi-step real-time fake detection process is picture preprocessing which entails resizing and normalizing the supplied currency note photos to ensure uniform input dimensions. In order to ascertain validity, the photos are subsequently run through the trained neural network models which examine characteristics like texture, printing quality and security markings. The streamlit UI displays the model's output which includes confidence scores and a determination of the currency note's authenticity (as shown in Fig.11).

Fig.11 User Interface

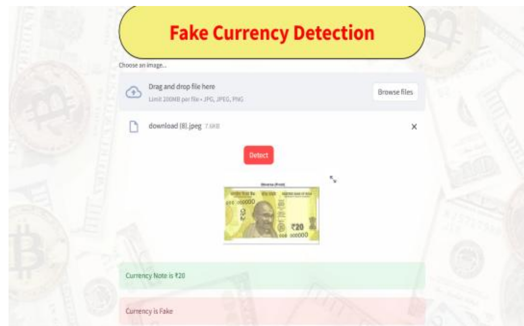

Fig.12 Real Time Predictions

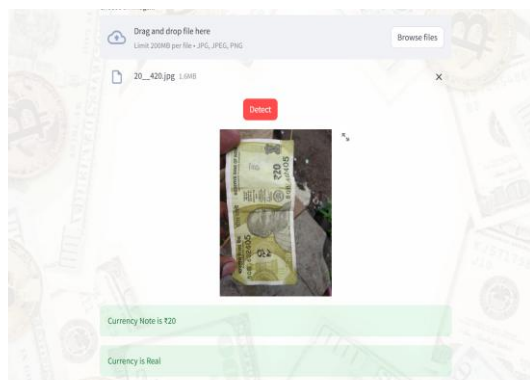

Fig.13 Real Time Predictions

The system's resilience was further assessed under various illumination scenarios and image quality fluctuations. Under ideal lighting circumstances the model distinguished between genuine and counterfeit notes with remarkable accuracy (as shown in Fig.12&13). However, the accuracy somewhat decreased, especially for ResNet-50 when low-resolution photos or bad illumination were used. Additional preprocessing methods including noise reduction and histogram equalization were used to improve image clarity in order to lessen these difficulties. This made guaranteed that the model remained very accurate even under less-than-ideal circumstances especially when using CNN and MobileNetV2. The outcomes and actual time evaluation of the system for detecting counterfeit currencies show how effective deep learning is in preventing financial fraud. MobileNetV2 is the most reliable model for real-world application with an excellent accuracy of 99.03%. CNN comes in second with a high reliability of 95%.

VI. CONCLUSION

The deep learning models CNN, MobileNetV2 and ResNet-50 were used to create a fake cash detection system which shows a highly effective and automated method of detecting counterfeit currency with impressive accuracy. With an accuracy of 99.03% MobileNetV2 is the most dependable model for real-time applications. CNN, on the other hand achieves 95% making it a formidable substitute for currency classification. ResNet-50 helps with extraction of features and deep neural network training for counterfeit detection even though its accuracy is only 74.03%. To ensure robustness across a range of image characteristics and lighting situations the system uses advanced methods for preprocessing such image normalization, scaling and augmentation. This technology reduces financial fraud and improves security measures in the financial and commercial sectors by combining deep neural networks and a simple user interface to facilitate smooth real-time detection and fast currency note authentication. In contrast to conventional detection techniques that necessitate manual confirmation or special tools, this AI-driven solution provides a quick, scalable, and easily accessible way that is especially advantageous for banks, individuals and businesses.

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