OPTIMIZING FAKE CURRENCY RECOGNITION THROUGH CNNS: A DEEP LEARNING PERSPECTIVE

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ABSTRACT

Recognizing counterfeit money is the process of locating it. For businesses and corporations, counterfeit cash is a serious issue because it can result in losses in funds and harm to their reputations. Examining various security measures on real cash notes is a common method for spotting counterfeit notes. These attributes include, among others, micro printing, color-shifting ink, and watermark. To identify fake currency in the past, currency notes were manually examined. However, this approach takes a lot of time, is prone to mistakes, and demands an extensive amount of knowledge. With the development of technology, computer-based techniques for identifying counterfeit money have become a viable option. In financial transactions, it is essential to find counterfeit money. Convolutional Neural Networks (CNN) has demonstrated outstanding performance in image identification tasks, including currency recognition, in recent years. This project offers a CNN-based method for identifying counterfeit money. The suggested method makes use of a dataset of photographs of actual and counterfeit money and prepares the images by shrinking, making them grayscale, and normalizing the values of the pixels. A CNN model is created by specifying the layers once the dataset has been divided into testing, validation, and training sets. On the basis of the training set, the model is developed, and the validation set is used to fine- tune the hyper parameters. Finally, the model's performance is assessed on the testing set. Experimental findings show that the suggested method detects counterfeit money with high accuracy, making it a promising method for preventing fraud in financial transactions.

KEYWORDS: Convolutional Neural Networks (CNN); Normalization, Currency Recognition; scanning with ultraviolet and infrared

1. INTRODUCTION

Identifying counterfeit cash is a crucial undertaking in the area of financial security that aims to find the notes and stop them from being circulated. Convolutional neural networks, also known as CNNs, have become a potent algorithm for recognizing images tasks, which makes them the best option for spotting counterfeit money. CNNs are excellent at automatically discovering and extracting significant information from photos, enabling precise classification between real and fake currency. The explanation of a CNN algorithm in this context entails describing the rationale for utilizing CNNs for counterfeit currency recognition, the importance of the issue, and the potential advantages of using CNNs in this field. The introduction starts off by stressing how common counterfeit money is and how it affects the economy. For people, companies, and governments alike, counterfeit currency can result in enormous financial losses. They weaken consumer confidence in financial systems, obstruct trade, and may even compromise national security. Therefore, it is crucial to create reliable ways for spotting counterfeit money. The introduction then goes through the shortcomings of conventional methods for identifying counterfeit money. The elaborate designs and variances contained in fake banknotes may escape the traditional approaches' reliance on handcrafted elements and rule-based techniques. Additionally, these techniques may take a lot of time and may not be very general to brand-new copycat patterns. This calls for the deployment of cutting-edge methods that can automatically discover and extract pertinent information from photographs of banknotes. The next section presents CNNs as a potential remedy. CNNs have completely changed how image identification tasks are done, and they have excelled in a number of fields, such as object detection, facial recognition, or medical imaging. In order to derive hierarchical representations of pictures, CNNs use numerous layers of interconnected neurons, simulating the visual decoding mechanism of the human brain. CNNs are highly suited for capturing the intricate textures, patterns, and minute characteristics that distinguish authentic banknotes from counterfeits because of their capacity to learn hierarchical structures.

The announcement also emphasizes CNNs' benefits in spotting counterfeit money. Without intentional feature engineering, CNNs may learn distinguishing features from a sizable collection of real and fake banknote images. Because of this, the algorithm can generalize well to new samples and is extremely adaptive to various counterfeit patterns. CNNs may also deal with fluctuations in light, scale, and introductions, which are frequent difficulties in banknote recognition. The introduction also stresses how financial systems' security measures can be improved and economic losses can be greatly decreased because to CNNs' high accuracy. In conclusion, the move to fake currency detection using CNN algorithm contextualizes the issue by emphasizing its importance, outlining the drawbacks of conventional methods, and proposing CNNs as a potent remedy. It highlights CNNs' capacity to automatically pick up on distinguishing traits, adjust to various counterfeiting patterns, and manage fluctuations in banknote pictures. This prepares the reader for the parts that follow, which explore the technical elements and CNN's algorithm's implementation in depth.

2. LITERATURE REVIEW/EXPERIMENTAL DETAILS

[1] Sun, Wie et al. have addressed the challenge of deploying image classification models on cloud computing platforms, especially as network depth and data volume increase. The complexity of these models, coupled with the computational demands of convolution processes, strains the GPU and storage resources of devices, particularly embedded and mobile terminals. To enable deployment on such devices, model compression becomes necessary. However, traditional compression methods often sacrifice global features, leading to reduced classification accuracy. To solve, this paper introduces a lightweight neural network model comprising twenty-nine layers, leveraging dilated and depth wise separable convolutions for image classification. By employing dilated convolution to expand the receptive field without increasing parameters, we extract higher-level semantic features, thus enhancing classification accuracy. Additionally, depth wise separable convolution reduces network size and computational complexity, while introducing parameters like width multiplier, image resolution, and dilated rate to ensure accuracy during compression.

[2] Rushikesh Jadhav, Swaraj Kalbande et al. recognizing currency and determining denomination relies on analyzing distinct attributes, be it physical properties like width and length or internal characteristics such as texture and color. While various methods have been proposed, some historical approaches lacked comprehensive authentication mechanisms. With technological advancements, particularly in

banking, self-servicing options have simplified transactions, including currency handling through recognition machines. However, existing recognition techniques, while convenient, may not sufficiently address authentication concerns. To mitigate this, newer methods, including the proposed YOLO-v3 CNN model-based system, offer fast and accurate banknote detection and recognition, catering to evolving needs in currency management and security.

[3] Park, Chanhum et al… implemented the technology to aid visually impaired individuals in identifying banknotes and coins via smartphone cameras has been a notable advancement. Prior efforts have utilized techniques like speeded-up robust features (SURF) for banknote detection, yet performance suffered under diverse backgrounds. Similarly, deep learning methods for counterfeit detection lacked seamless integration into smartphone applications. To overcome these limitations, this paper introduces a three-stage detection technology employing faster region-based CNN, geometric constraints, and residual networks (ResNet). This approach enhances performance across varying environmental conditions, fulfilling the critical need for accessible currency recognition tools for the visually impaired.

[4] Pham, Tuyen Danh et al. despite advancements, challenges persist in automating banknote handling tasks, including denomination recognition and counterfeit detection. Counterfeit bills pose a significant threat to transaction security, necessitating robust detection mechanisms. Existing anti-counterfeit technologies, while diverse, face limitations in practical implementation due to the complexities of detection techniques. Automatic recognition methods, often integrated into sorting machines, rely on specialized sensors or imaging sensors to identify counterfeit banknotes. This research contributes to this field by proposing novel approaches to counterfeit detection, leveraging advanced imaging techniques and specialized algorithms for enhanced accuracy and reliability.

[5] Joshi, Rakesh Chandra et al. enhancing medical diagnosis affordability and accessibility has been a driving force behind technological innovations in healthcare. However, the focus on aiding individuals with disabilities, particularly visual impairment, remains an urgent priority. Currency recognition poses a significant challenge for the visually impaired, given the diverse characteristics of banknotes. Currencies play an important role as a medium or a transaction to have goods and services. Every country has their own currency in different denominations, which differs in color, size, shape and pattern. It becomes very difficult for any visually impaired to recognize and count the currency in different denomination. Traditional tactile markers on banknotes degrade over time, further complicating identification by touch. Digital image processing offers a viable solution to this challenge, enabling the development of systems like this proposed YOLO-v3 CNN model-based banknote detection and recognition system. This system facilitates fast and accurate recognition, empowering visually impaired individuals with greater independence in managing financial transactions.

Furthermore, ongoing research aims to refine CNN architectures and methodologies for currency detection, exploring techniques such as attention mechanisms and hybrid approaches. These advancements seek to further improve the accuracy and reliability of CNN-based counterfeit detection systems, ultimately contributing to enhanced financial security and fraud prevention. Techniques such as attention mechanisms, which enable CNNs to focus on salient regions of banknote images, are being explored to improve detection performance. Moreover, hybrid approaches that combine CNNs with other machine learning techniques, such as spectral analysis or ensemble methods, are being investigated to leverage complementary strengths and achieve even higher levels of accuracy.

The current systems for identifying counterfeit money can be broadly divided into two categories: computer- based methods and manual inspection. Genuine currency notes have a variety of security measures, including a watermark, a safety a thread, color-shifting ink, plus micro printing, which are all visually inspected during manual inspection. This approach takes a lot of time, requires a lot of knowledge, and is error prone. Contrarily, computer-based techniques employ computer vision and machine learning algorithms to detect counterfeit money automatically. The two categories of these techniques are based on features as well as deep learning-based approaches. Features like texture, color, and shape that are present in real currency notes are extracted using feature-based techniques. Then, in order to distinguish between legitimate and fake cash, these attributes are fed into a computerized classification algorithm, including Support Vector Machines, or SVM, or Random Forest. There are other commercial hardware and software options for recognizing counterfeit currency in along with the methods outlined above. These solutions frequently combine several distinct methods, such as scanning with ultraviolet and infrared light, analyzing with magnetic and ink, and visually inspecting security features.

LIMITATIONS

- The manual method is laborious, needs specialized training, and occasionally fails to detect well-made knockoffs.
- High initial costs: Especially for small firms or organizations, stablishing computerized procedures for counterfeit currency identification can be expensive.
- Limited effectiveness: Not all counterfeit currency can be detected by automated systems, particularly when it comes to well-made and challenging-to-find examples.

3. RESULT AND DISCUSSION

3.1 Concept

The process of distinguishing fake currency notes from real currency notes is known as fake currency recognition. This is a crucial step in financial transactions since fake currency may cost people and companies a lot of money. The detection of counterfeit money can be done using a variety of techniques, such as visual examination of security features, scanning with ultraviolet and infrared light, magnet and inkjet analysis, and computer- based techniques utilizing machine learning algorithms like CNN (Convolutional Neural Networks). The collection of a dataset of actual and counterfeit cash photos is the initial stage in the suggested method. The dataset needs to be large enough to supply the CNN model with enough training instances, and it should be diverse, comprising pictures of various types and denominations of currency.

The photos are preprocessed after the dataset has been gathered to get them ready for training. In order to limit the quantity of data the CNN model must analyze and to increase the reliability and rapidity of the training process, this entails scaling the images to a constant size, turning them to grayscale, and normalizing the pixel values. The dataset is then divided into the training, confirmation, and testing sets. The CNN model is trained using the training set to distinguish between photos of real and counterfeit cash. In order to prevent overfitting, the set of validation parameters is used to adjust the hyper parameters of the model, including the rate of learning and batch size. The training model's performance on untrained data is assessed using the testing set. By specifying the model's layers and architecture, the CNN model is created. To learn the characteristics and categories the images, this often entails stacking numerous layers using convolution, layer pooling, and fully connected layers. The algorithm proceeds to train on the training data using an optimization approach to minimize the loss function, including random gradient descent or Adam. The proposed framework is shown in fig 1.

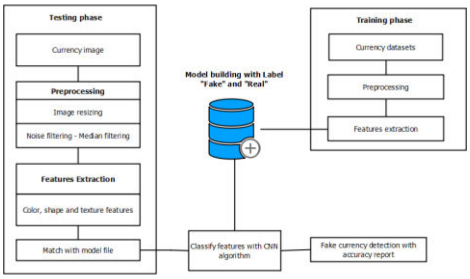

Fig. 1. Proposed Architecture

3.2 Algorithm

Convolutional neural network algorithms (CNN) are an efficient algorithmic solution for automatically identifying fake banknotes in fake cash detection. The CNN algorithm includes a number of crucial processes that allow precise differentiation between real money and counterfeit money. Creating a library of banknote images that includes both authentic and fake examples is the first stage. This dataset ought to be diverse and representative, taking into account different denominations, angles, lighting setups, and patterns of fake money. The testing, validation, and training sets are then created from the dataset. The note images are then preprocessed to make it easier for the CNN model to be trained and execute. Images may be resized to a constant resolution made grayscale to facilitate processing, and their pixel values normalized to a set scale as part of preprocessing processes. By specifying the neural network's architecture, the CNN model is built. A CNN typically comprises of a number of pooling layers, fully connected layers, and convolutional layers.

The input images are subjected to filters by the convolutional layers, which then extract features like edges, textures, and patterns. The feature maps' spatial dimensions are decreased by the pooling layers' down sampling. These retrieved features are used by the fully connected layers to provide predictions. The training procedure starts when the model architecture has been established. The training set is used to teach the CNN model how to identify the characteristics that distinguish real currency from counterfeit. Forward propagation, in which the model produces forecasts based on the current variables, and back propagation, in which the model modifies the parameters based on the estimated loss in order to reduce error, is both steps in the training process. Usually, a suitable loss function and gradient descent are used to carry out this optimization process. The set of validation data is employed in order to adjust the model and avoid overfitting. It is helpful to choose the appropriate hyper parameters that such as learning rate, the number of batches, and regularization methods, based on the model's performance on the validation set. The CNN architecture is shown in fig 2.

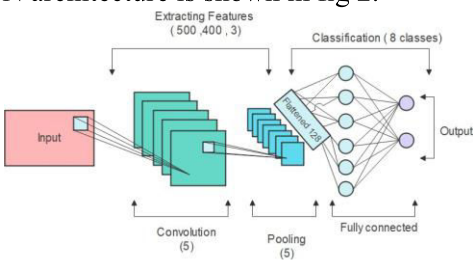

Fig. 2. CNN Architecture

3.3 Modules Description

Datasets Acquisition

The user can enter the currency note in this module. An image or camera capture may be used as input. Money may vary in terms of color, shape, and other characteristics. Images of Indian money notes in various denominations can be found in the Indian money collection, a publicly accessible collection. A total of 6000 photos makes up the collection, 1000 images for each rupee value of 10, 20, 50, 100, 200, 500, and 2000.The dataset is more varied and difficult because the photographs were taken with several cameras under various lighting conditions. Images of the currency notes' reverse sides are also included in the dataset, which gives machines with learning models extra data. The dataset is ideal for unsupervised machine learning techniques because it is labeled with the value of each currency note. The dataset is frequently used to test and train artificial intelligence models for problems involving currency recognition. For researchers and programmers in India who are developing apps for currency recognition, the Indian Monetary Dataset is an invaluable tool. It gives users access to a realistic and varied collection of photos that can enhance the robustness and accuracy of artificial intelligence models.

Preprocessing

Preprocessing, within the realm of image analysis, encompasses the actions taken to prepare an image for further analysis or processing. This crucial step aims to enhance accuracy and suitability for various image processing tasks by cleaning, converting, and normalizing the image data. Common preprocessing techniques include cropping, scaling, noise reduction, histogram equalization, and normalization. The specific methods employed depend on the task at hand and the characteristics of the image being processed. In the context of currency recognition, preprocessing plays a vital role in improving the quality of input data and enhancing the accuracy of learning models. Here are some typical currency recognition preprocessing steps: Image resizing: Resizing the pictures to a standard size is the initial step in preprocessing. To guarantee that all photos have identical dimensions and aspect ratio, this is crucial. By doing so, the model's computational complexity can be decreased and its effectiveness increased.

Normalization

The process of bringing the image's pixel values within a predetermined range is known as normalization. This can enhance the image's contrast and brightness and make it simpler for the model to pick out key details.Noise removal: Currency photos frequently have noise and artefacts that might make it difficult for the model to distinguish between crucial details. To reduce noise and enhance the quality of the photos, noise removal techniques like Gaussian smoothing out, average filtering, and thresholding of images can be utilized.

Features Extraction

Convolutional neural networks, also known as CNNs, are a tool in computer vision that is used to extract useful and instructive information from digital images. In this procedure, a set of characteristics are extracted from the input image using a pre-trained CNN. These features, which the CNN learns and refines throughout the training process, can be applied to a variety of computer vision applications, including segmentation, object identification, and image classification. We may extract features like form, color, and texture feature values in this module. The preprocessed pictures of the cash notes are used to train the CNN model. The model's convolutional layers extract different information from the images during training. The texture, color, and other qualities of the banknotes are captured by these features.

Model Training

Convolutional neural networks, also referred to as CNNs, are a machine learning technique that may be used to train models for computer vision applications including object identification and picture classification. Here is a general description of what happens: Preparation of data Split the information into validation and training sets, add further data, and normalize the data to prepare the graphic data for training. What is the model architecture? A custom architecture should be created based on the task's unique requirements and an appropriate CNN architecture. Assemble the model Define the measurements to be utilized during training, as well as the optimizer and loss function. Model training: Using the specified optimizer, the loss function, and metrics, trains the model using training data by putting the images through the network while updating the weights. Multiple iterations, often referred to as epochs, of the training process over the data used for training are required in order to get the desired degree of accuracy.

Currency Classification

Label the currency using the CNN framework in this module, which involves the following steps: certify the model: To prevent overfitting and to make sure the model is adapting adequately to new data, assess its efficacy on the validation data. Adjust the model: Modify the algorithm's architecture, hyper parameters that or training process based on the validation results to boost the model's performance. Continue doing this until the desired precision is attained. Analyze the model: To get a fair approximation of the model's performance on unlabeled data, assess the model's performance on a different test set. Give the accepted money note as a final proof, real or phony.

3.4 Experimental Results

A dataset of real and fake banknote pictures would be gathered in an experimental setting for CNN-based fake cash detection. A set for training and a set to be tested would be the two main components of this dataset. In order for the CNN model to acquire and derive pertinent information from the images of banknotes; it must be fed the training set during the training phase. Convolutional layers, layers for pooling, and completely connected layers are often included in the model's architecture, which is made to automatically learn and record the designs, textures, including structures that distinguish authentic banknotes from counterfeits. Through methods like back propagation thereby gradient descent, the parameters of the model are optimized during training with the goal of reducing the loss function and enhancing the model's capacity for precise prediction. The testing step starts once the CNN model has been trained. The performance of the model is assessed using the testing set, which includes banknote images that were not present during training. Each banknote picture in the testing set is predicted by the model to be either genuine or counterfeit. The effectiveness and accuracy of the model are then evaluated by comparing the predictions to the ground truth tables. The performance of the system can be shown in fig 3 and 4

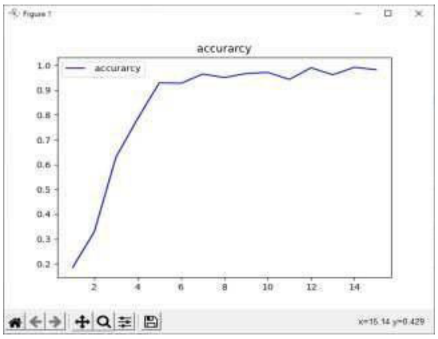

Fig. 3. Accuracy Chart

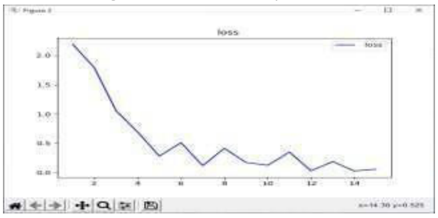

Fig. 4. Loss Chart

4. CONCLUSION

In conclusion, identifying counterfeit money is crucial in financial transactions because it can result in huge losses for both firms and people. Visual inspection, infrared and ultraviolet scanning, and other conventional techniques for identifying forged currency might take time and require specialized tools. As they are able to learn to extract information from photos and identify them as real or counterfeit, Convolutional Neural Networks have demonstrated promising results in the recognition of false cash. Creating a diverse collection of photos, preprocessing them, developing the CNN model's architecture, extracting characteristics from the images, validating and fine-tuning the algorithm, then testing and evaluating the model's correctness are all steps in the note feature extraction process using CNN. Using CNN to extract note features has a number of advantages over more conventional techniques for identifying counterfeit money, including its accuracy in classifying notes or its ability to adapt to new and varied datasets. The caliber of training data, the CNN architecture selected, and the model's hyper parameters all affect how well the CNN model performs. In conclusion, employing CNN for fake cash recognition is a promising method for enhancing the process's precision and effectiveness. It is possible to correctly categories photos of cash notes and lowers the likelihood of fraudulent activity in financial transactions by using CNN-based algorithms to extract attributes from the images.

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