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Review Article

Neural Guard: A Deep Learning Framework for Currency Fraud Detection

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Abstract

This review paper explores the increasing utilisation of deep learning techniques in currency verification, with a focus on identifying and preventing counterfeit Indian rupees. Counterfeit currency continues to pose a significant danger to the economic stability of nations globally, including India. Conventional detection approaches are constrained by their reliance on manual examination and their vulnerability to human error, rendering them ineffective for extensive or real-time applications. Deep learning has emerged as an effective option, utilising sophisticated algorithms to effectively detect counterfeit currency with minimal human involvement. The research methodically analyses various deep learning and machine learning models that demonstrate potential in currency verification, especially in the precise and efficient detection of counterfeit notes. Prominent among these are Convolutional Neural Networks (CNNs), recognised for their formidable image-processing skills. Convolutional Neural Networks (CNNs) can scrutinise intricate visual patterns in cash, rendering them exceptionally adept at detecting nuanced distinctions between authentic and counterfeit notes. Moreover, Support Vector Machines (SVM) and Random Forest algorithms are emphasised for their efficacy in classifying money photos based on various criteria. Recent and advanced models, like MoBiNet and ResNet-50, are examined, emphasising their ability to perform real-time money authentication tasks. The review examines the potential of these technologies to assist visually impaired individuals by facilitating automated currency identification systems that audibly verify the authenticity of banknotes.

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1. INTRODUCTION

Currency authentication is essential for maintaining the integrity and stability of economic transactions. In economies characterised by frequent and extensive financial transactions, the existence of counterfeit currency can profoundly erode trust in the financial system, resulting in considerable economic consequences [10]. Counterfeit currency leads to immediate financial losses for enterprises and consumers while also intensifying larger problems like corruption and the proliferation of illicit funds. These unlawful acts can disrupt market dynamics, raise prices, and enable illegal organisations, ultimately destabilising the economy and undermining public trust. Conventional techniques for cash verification predominantly depend on discernible security attributes integrated into banknotes [2]. These attributes encompass security threads, watermarks, holograms, colour-shifting inks, and complex microprinting. Although these methods offer a first protection against counterfeiting, their efficacy is progressively undermined by developments in colour printing and duplication technologies. Contemporary counterfeiters have mastered the replication of these security features, creating counterfeit currency that seems authentic even to experienced examiners [5]. The continuous arms race between the advancement of security features and counterfeiting tactics underscores the pressing necessity for increasingly sophisticated and robust authentication mechanisms.

In this regard, deep learning methodologies offer a viable solution to improve currency authentication systems. This research seeks to examine the utilisation of deep learning techniques, particularly Convolutional Neural Networks (CNNs), transfer learning, and diverse machine learning algorithms in enhancing the precision and accessibility of currency authentication [7]. Convolutional Neural Networks (CNNs) excel in processing and analysing intricate patterns and textures in images, allowing them to detect small differences between authentic and counterfeit currency that may be undetectable to human observers. Transfer learning utilises pre-trained models on large datasets, facilitating the swift adaptation of these models to the specific intricacies of currency detection without requiring substantial retraining. Moreover, diverse machine learning algorithms can augment deep learning methodologies by offering strong classification and feature extraction abilities, hence improving the overall precision of authentication systems [6].

Furthermore, the use of these sophisticated techniques can facilitate the creation of more accessible and user-friendly authentication instruments. Smartphone applications employing deep learning can enable individuals and organisations to authenticate currencies in real-time, diminishing dependence on specialised equipment and improving security in routine transactions [8]. Enhancing the precision and availability of currency verification by deep learning can substantially alleviate the threats posed by counterfeit cash, therefore preserving economic stability and diminishing the incidence of illicit funds and corruption.

This thorough assessment will assess the present status of deep learning applications in currency authentication, emphasise the gains made, and pinpoint the obstacles that persist [11]. Addressing these difficulties through ongoing research and innovation is essential for creating more reliable and efficient solutions for counterfeit protection, thereby reinforcing the economic framework and maintaining the integrity of financial transactions.

Literature

1. In their 2021 work "Fake Currency Detection with Machine Learning Algorithm and Image Processing," Bhatia, Kedia, Shah, and Kumar examine the application of machine learning algorithms and image processing techniques for the detection of counterfeit currency [1]. This paper, presented at the 5th International Conference on Intelligent Computing and Control Systems, examines strategies to combat the escalating problem of currency counterfeiting, which endangers economic security and necessitates more effective and dependable detection systems [1].

The authors utilise several machine learning methodologies in conjunction with image processing to examine money characteristics and discern indicators exclusive to genuine notes. The research emphasises the application of algorithms, including Support Vector Machines (SVM), for classification purposes, augmented by feature extraction methods such as edge detection and texture analysis. These procedures allow the model to distinguish between authentic and counterfeit currency based on certain, measurable visual attributes. The machine learning model is trained to identify authenticity indicators in high-resolution images of currency notes, including watermark placement, texture consistency, and the presence of security threads, which are difficult for counterfeiters to accurately replicate [6].

This paper's principal contribution is its implementation of a straightforward yet efficient method for feature extraction and classification, adaptable to diverse currency types. The model exhibits potential for high accuracy; however, the authors recognise limits regarding processing speed and the necessity for clear, high-quality images to achieve optimal performance. This study establishes a basis for subsequent research on the integration of deep learning models that may improve accuracy and facilitate real-time detection in mobile or portable applications, thereby expanding the practical use of machine learning in counterfeit prevention [7,11].

2. In the 2017 study "Fake Currency Detection Using Image Processing," Agasti and associates examine the utilisation of image processing methodologies for the critical problem of counterfeit currency identification [2]. The work, published in the IOP Conference Series: Materials Science and Engineering, underscores the necessity for enhanced automated detection methods due to the growing complexity of counterfeiting technology. Conventional visual screening techniques, dependent on human identification of currency security attributes, frequently prove inadequate against high-quality counterfeits,

underscoring the necessity for more dependable technological alternatives [8].

The researchers delineate a methodology grounded in digital image processing, encompassing critical phases such as edge detection, segmentation, and feature extraction. These techniques enable the system to recognise and isolate distinct visual characteristics inherent to genuine currency notes, including watermarks, security threads, and micro-texts. Edge detection is essential for identifying authentic notes by recognising curves and other characteristics that counterfeiters frequently find difficult to copy accurately [7]. Segmentation improves accuracy by partitioning the monetary image into smaller sections, each evaluated for consistent patterns and textures that signify authenticity.

A key contribution of the paper is its emphasis on accessible, computationally efficient methodologies suitable for implementation across many applications, including portable and mobile platforms. The authors propose a system that utilises common image processing techniques, making it both cost- effective and adaptable to other currency types [12]. The authors recognise that, despite the approach's potential, it has limits in managing low-quality photos and intricate counterfeit characteristics. They propose further research avenues, including the incorporation of machine learning or deep learning techniques to augment robustness and adaptability, hence enhancing the accuracy and efficiency of counterfeit cash detection systems. This research establishes a significant foundation for the creation of automated, scalable systems that may function as essential instruments in combating counterfeiting.

3. In their 2022 paper, "Real-Time Fake Note Detection Using Deep Convolutional Neural Network," Kakade, Sinha, Kachare, and Shinde investigate the efficacy of deep learning for the real-time identification of counterfeit currency. This study, published in IEEE Xplore, examines the application of deep convolutional neural networks (CNNs) to combat the increasing complexity of counterfeiting techniques that conventional manual and semi-automated systems cannot address. The model's real-time capacity is a significant development, designed to deliver precise and instantaneous verification in environments such as banks, retail establishments, and ATMs [3].

The authors propose a CNN-based method that utilises high-dimensional feature extraction to identify complex characteristics in cash photos. Through training the model on a varied dataset of authentic and counterfeit cash photos, the CNN acquires the ability to identify distinct patterns, textures, and characteristics that distinguish genuine notes from fraudulent ones. This methodology enhances previous machine learning models that depended on rudimentary methods and frequently exhibited constraints in accuracy and scalability [6]. The CNN's capacity to autonomously extract pertinent features diminishes the necessity for manual feature engineering, enhancing the system's adaptability to diverse currency sorts and varying counterfeiting methods [5].

The capability for real-time processing is attained by an efficient network design, guaranteeing swift analysis while maintaining accuracy. The research demonstrates favourable outcomes regarding detecting speed and precision, rendering it suitable for practical application in high-traffic settings where rapid cash verification is critical. Nonetheless, the authors address issues, including the necessity for high-quality photographs and the possible effects of visual distortions in practical applications.

The authors propose further work that entails additional model improvement to improve resilience to fluctuations in lighting, angle, and image quality. This research demonstrates that deep CNNs are effective for real-time currency authentication, facilitating scalable, automated solutions to decrease the global economic impact of counterfeit currency. [5]

4. In their 2023 paper, "Indian Currency Fake Note Detection System Using ResNet-50," Shinde, Yadav, Singh, and Jiwane present an advanced deep learning methodology aimed at improving the precision and efficacy of counterfeit currency detection for Indian banknotes [4]. This paper, published in IEEE Xplore, examines the utilisation of ResNet-50, a robust convolutional neural network architecture recognised for its depth and superior performance in image identification applications. The ResNet-50 model is adept at processing intricate visual data, enabling it to scrutinise subtle features in currency notes that are frequently difficult to discern manually or with conventional machine learning models. [8]

The authors employed ResNet-50 because of its profound, 50-layer architecture, which excels in discerning complex patterns and nuanced differences between authentic and counterfeit currency. Through training on a dataset of genuine and counterfeit Indian currency photos, the model acquires the ability to distinguish between legitimate security features and prevalent counterfeiting indicators. The stratified method of feature extraction enables ResNet-50 to discern both overarching and intricate features, including watermark locations, textural variations, and the existence of latent pictures, which are essential for differentiating authentic notes from counterfeits.

The ResNet-50-based system exhibited exceptional accuracy and resilience during testing, indicating substantial potential for use in practical scenarios, including ATMs, retail, and banking industries, where swift and dependable cash verification is crucial. The model's intricate architecture enables a high level of accuracy, hence substantially mitigating the likelihood of false positives and false negatives.

The study identifies certain constraints, including the necessity for high-resolution photos and consistent lighting conditions, as fluctuations in these elements may impact model performance. The authors propose that future research may involve modifying models for enhanced resilience in suboptimal situations and incorporating mobile platforms to augment accessibility. This study represents a notable progression in counterfeit identification, illustrating the applicability of ResNet- 50 for practical and scalable cash authentication [8].

5. Conventional Techniques in Currency Authentication

Conventional money authentication techniques depend on security attributes that may be validated via manual examination. These characteristics encompass latent images that reveal themselves upon tilting a banknote; micro-lettering, which consists of minuscule writing discernible alone under magnification; and optically variable inks that alter colour depending on the viewing angle. Although these systems offer a fundamental degree of protection, they lack reliability and scalability, particularly against progressively advanced counterfeiting tactics [5]. Counterfeiters increasingly employ sophisticated printing methods to replicate these obvious security elements, complicating the accurate differentiation between genuine and counterfeit notes through physical inspection alone. [4] Consequently, conventional procedures are frequently labour-intensive and susceptible to human error, especially when applied on a big scale. This underscores the necessity for sophisticated, automated solutions, such as those provided by deep learning, to guarantee more reliable and efficient currency authentication.

6. Machine Learning Approaches

Initial machine learning endeavours in currency authentication predominantly utilised basic algorithms, resulting in only middling accuracy due to inherent constraints. A study by Bhatia et al. (2021) employed fundamental image processing techniques to discern unique characteristics of banknotes, utilising a restricted dataset for model training [6]. Despite being innovative at the time, these initial models were limited in their ability to identify only basic, superficial characteristics in cash photos. They lacked the expertise to discern intricate patterns, textures, or subtle characteristics that differentiate authentic notes from counterfeit ones. Moreover, computing constraints at that time hindered the models' efficacy, as the available hardware frequently lacked the capacity to manage more complex algorithms or larger datasets. The aforementioned restrictions rendered early machine learning algorithms incapable of efficient scaling or adaptation to the progressively intricate counterfeit methods, underscoring the necessity for more advanced deep learning approaches in subsequent years [11].

7. Deep Learning in Fake Currency Detection

Recent research in currency authentication increasingly utilises deep learning algorithms, which have considerably enhanced the field by their ability to identify patterns and extract complex data. Convolutional Neural Networks (CNNs) have shown to be essential for their efficacy in processing high- dimensional visual data, rendering them suitable for analysing intricate textures and subtle signs of validity in bank notes. The application of CNN models facilitates the automatic recognition of intricate patterns and distinctive features that are difficult to discern using conventional techniques. Moreover, transfer learning methodologies, particularly those employing the EfficientNet architecture, have exhibited significant potential by attaining both elevated accuracy and rapidity in distinguishing authentic from counterfeit currency. This is particularly advantageous when extensive and swift validation is necessary [7].

Furthermore, research conducted by Agasti et al. (2017) highlights the significance of edge detection and image segmentation in the authentication process. These technologies facilitate the isolation of certain features and improve image processing, guaranteeing the detection of even tiny variations between authentic and counterfeit notes.

8. Advanced Algorithms

Support Vector Machines (SVM): Support Vector Machines (SVM), a prevalent supervised learning model, have been utilised in money authentication jobs, specifically for the classification of currency images. Support Vector Machine (SVM) operates by identifying an ideal hyperplane that delineates distinct classes within a dataset, rendering it effective for identifying counterfeit currency based on identifiable characteristics. The binary classification method of SVM limits its effectiveness to basic counterfeit indications, as it may have difficulties in distinguishing between many classes in more intricate scenarios that necessitate high-dimensional feature analysis. [12]

Random Forest Classifier: The Random Forest classifier, recognised for its high accuracy and robustness, has demonstrated effective performance in applications necessitating accurate categorisation, including counterfeit identification. This model functions by creating an ensemble of decision trees, each trained on random subsets of data and features, subsequently aggregating their predictions for a conclusive judgment. Random Forest is proficient in converting input data into

higher-dimensional feature spaces, facilitating the accurate detection of tiny differences in money notes, which is crucial for distinguishing authentic from counterfeit [8].

MoBiNet and ResNet-50: MoBiNet, an amalgamation of MobileNet and Binary Neural Networks, together with ResNet-50, has been effectively used for cash authentication on mobile platforms, delivering efficient processing with diminished computing demands. MoBiNet is designed for lightweight applications, facilitating real-time authentication with reduced power consumption, rendering it suitable for mobile cash authentication tools. ResNet-50, using a 50-layer architecture, excels at extracting intricate visual elements from high-resolution currency photos. This depth enables ResNet-50 to discern detailed details, essential for detecting subtle counterfeit indications. Its adaptability for mobile use highlights its potential in creating accessible, portable, and dependable authentication solutions [9].

DenseNet 121: Convolutional networks with shorter connections between layers near the input and those close to the output can be significantly deeper, more effective to train, and more accurate, which is why this network was proposed [3].

The thick Conv Net is a feed-forward network that connects each subcaste to every other subcaste. Each subcaste receives as input the point maps it has learned. DenseNet121 offers colourful benefits: they break the evaporating grade problem, ameliorate point propagation, and substantially reduce the number of hyperparameters.

A deep learning model called DenseNet-121 can be used for image-based classification to tell the difference between real and fake currency notes [11].

High Accuracy: Pre-trained DenseNet-121 models have strong image classification performance.

Transfer Learning: Can be improved for quick and accurate detection on currency datasets.

Extraction: Captures intricate features like patterns, textures, and watermarks from currency notes. The above software is used in the proposed Implementation. Various methods can be adopted to identify a currency and to check its originality. Although many methods have been discussed in the past to identify fake currency, only those methods that are speedy and accurate in the currency's originality are adopted.

PROPOSED SYSTEM:

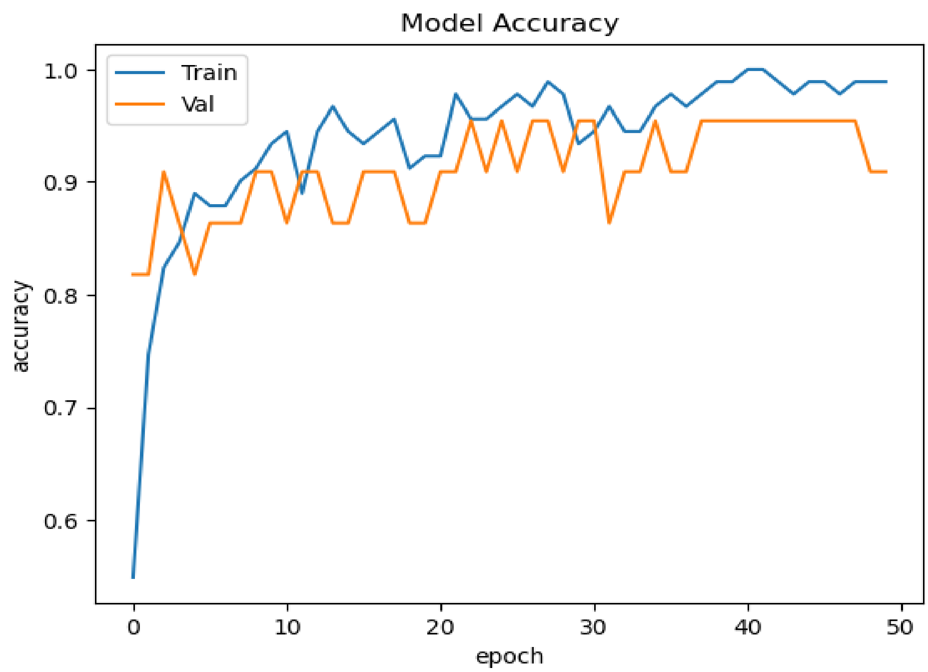
Transfer Learning Model as Training Model

Transfer learning can be applied in two ways. First, Fine-tuning: In fine-tuning, the pre-trained model is adapted to the new task by retraining some or all of the model's layers on the new dataset. Typically, the earlier layers of the pre-trained model are frozen, while the later layers are retrained to learn task-specific features. Second, Feature extraction: In feature extraction, the pre-trained model is used as a fixed feature extractor, and the output of one or more layers of the model is used as input to a new model trained on the new dataset.

Deep Learning Models Overview

Used a CNN model

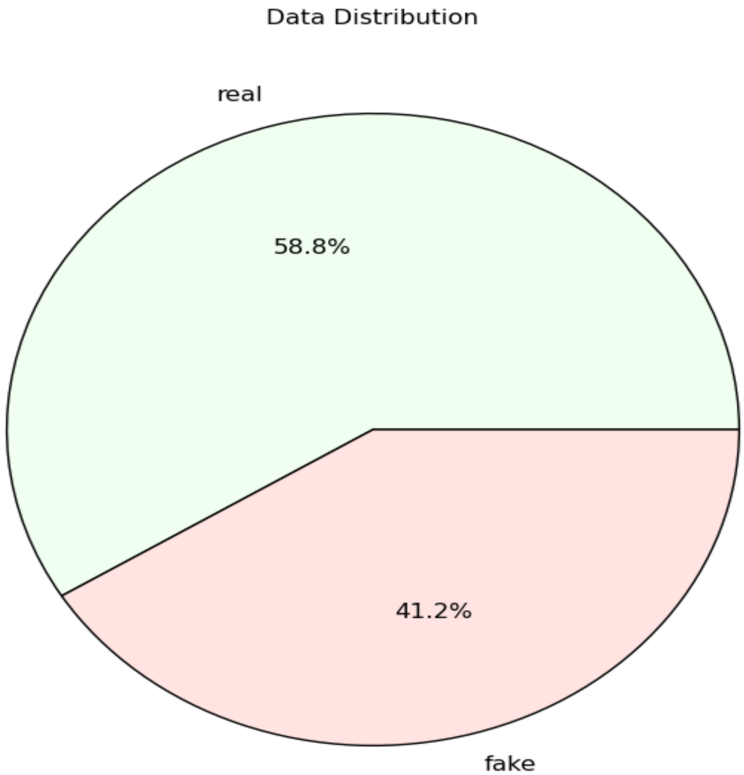
CNNs have fundamentally changed our approach towards image recognition as they can detect patterns and make sense of them. They are considered the most effective architecture for image classification, retrieval and detection tasks as the accuracy of their results is very high.

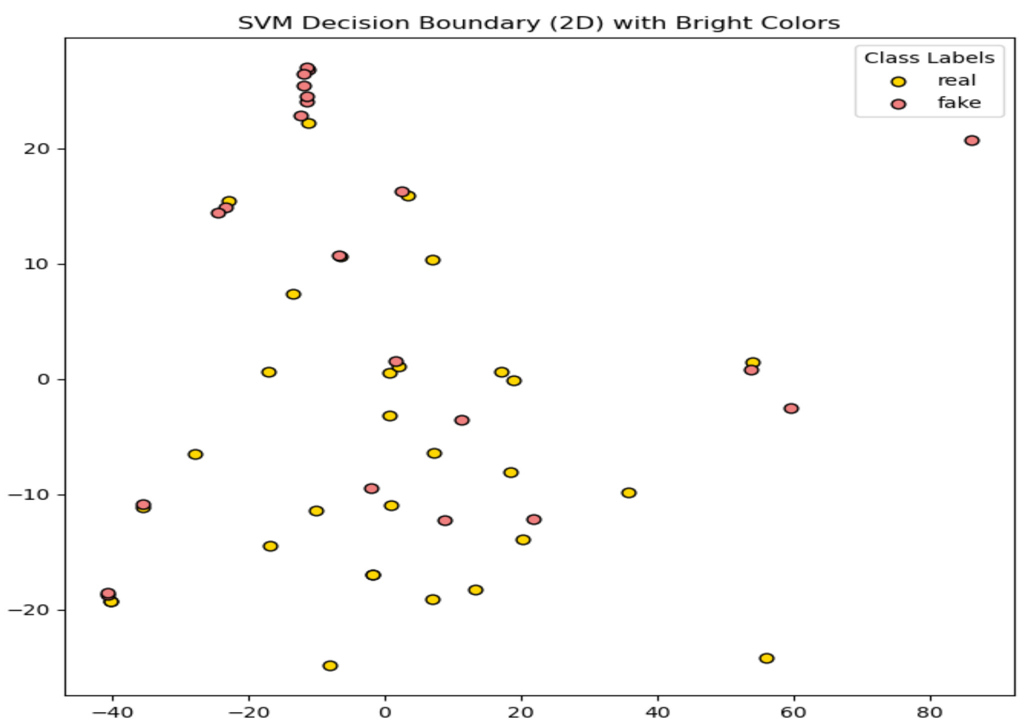


Generating classification report

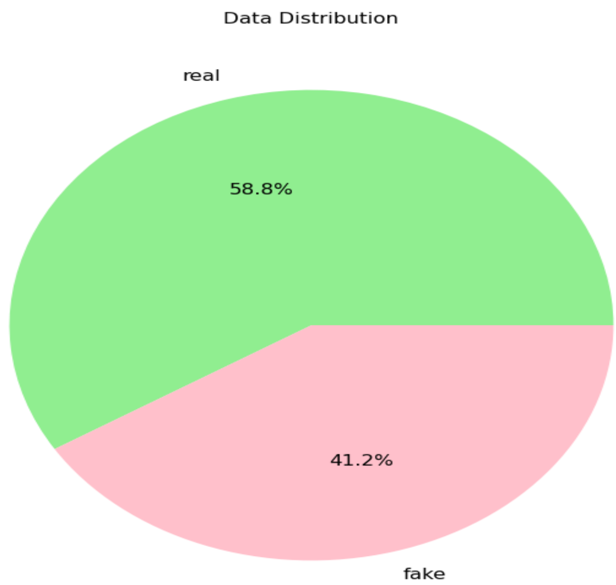
print (classification report (y _test, y _pred, target names = ['fake', 'real']))				
	precision	recall	f1-score	support
fake	0.67	1.00	0.80	4
real	1.00	0.89	0.94	18
accuracy			0.91	22
macro avg	0.83	0.94	0.87	22
weighted avg	0.94	0.91	0.92	22

Used SVM classifier:
(SVMs), Occasionally referred to as support-vector networks, stand as supervised learning Models equipped with corresponding learning algorithms. On-probabilistic binary linear classifiers are what the SVM training algorithm creates to classify fresh instances.



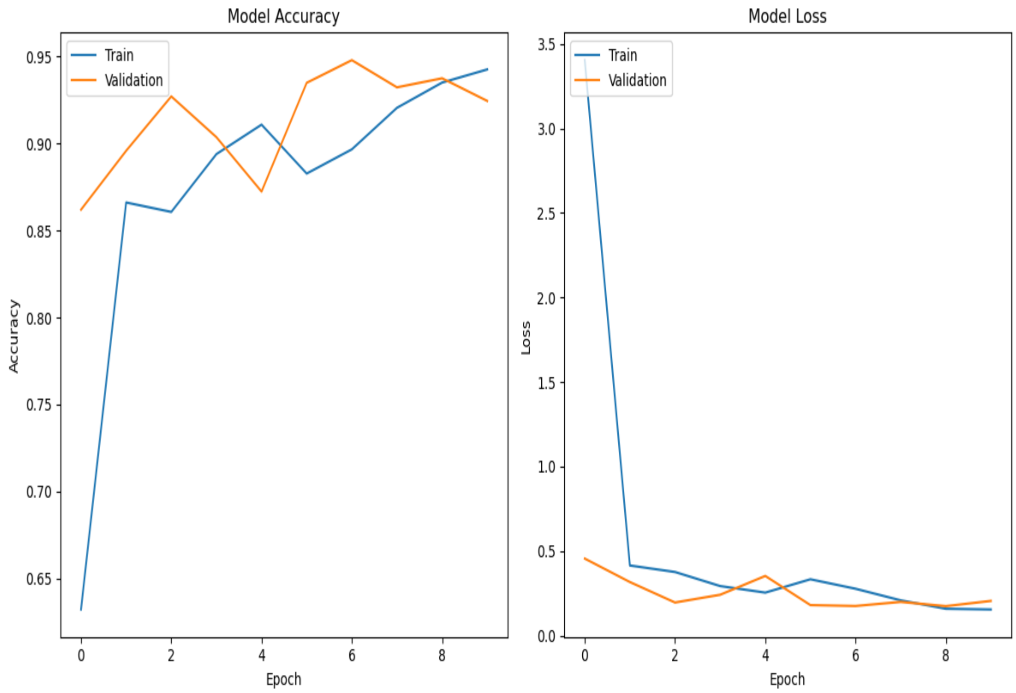


Used Random Forest Algorithm:
Transformation of the original input set to higher dimensional feature space is done using the kernel function of RFA (Bhatia et al. 2021), to use the hyperlink, which is required for the RFA algorithm. The advantage of RFA is that it requires less training data when compared to other models. The detection of currency notes data sets improves the accuracy by a greater rate.



Used MoBiNet classifier:
To tackle this training issue, we propose a novel neural network architecture, namely MoBiNet - Mobile Binary Network, in which skip connections are manipulated to prevent information loss and vanishing gradient, thus facilitating the training process.

DenseNet 121: Convolutional networks with shorter connections between layers near the input and those close to
The affair can be significantly deeper, more effective to train, and more accurate, which is why this network was proposed.
A deep learning model called DenseNet-121 can be used for image-based classification to tell the difference between real and fake currency notes.



2. METHODOLOGY

Modern deep learning models frequently employ transfer learning for effective money authentication, utilising pre-trained models to expedite the training process and enhance performance on specific tasks, such as counterfeit currency detection. In currency authentication, widely used pre-trained models such as EfficientNet and ResNet-50 are modified to address the distinct visual characteristics seen in currency notes. These models, initially trained on extensive image datasets such as ImageNet, have acquired the ability to identify diverse visual patterns and can be fine-tuned for particular applications, such as differentiating authentic cash from counterfeit notes.

Fine-tuning is an essential component of transfer learning. This technique involves fine-tuning the layers of the pre-trained model to enhance the identification of specific characteristics present in currency, including watermarks, security threads, micro-letters, and complex patterns that are challenging for counterfeiters to correctly reproduce. Fine-tuning generally entails training solely the last layers of the network while preserving the integrity of the preceding layers, which have already acquired fundamental properties beneficial for image identification. This enables the model to acquire more specific representations without the necessity of training from the beginning, conserving both time and computational resources.

A vital technique is featuring extraction, in which the pre-trained convolutional layers of the model are employed to analyse and derive significant visual features from the currency images. The collected characteristics are further processed by additional classifiers, including Support Vector Machines (SVM) or Random Forest, for the last stage of currency verification. This multi-faceted methodology, integrating pre-trained models for feature extraction with specialised classifiers for conclusive validation, guarantees elevated precision in identifying counterfeit currency, even in intricate or diverse situations. These methodologies render transfer learning an effective instrument for developing efficient and scalable currency authentication systems.

Analysis of Existing Systems and Approaches: System Limitations

Contemporary currency authentication solutions are mostly engineered to operate within a singular language, frequently emphasising a distinct array of security attributes pertinent to a certain kind of money kind or language. This monolingual attitude considerably restricts the models' capacity to process and verify currencies that exhibit numerous languages or geographical variances. In nations such as India, where currency notes incorporate many languages, these models may struggle to identify or accurately interpret multilingual elements, including text and symbols presented in various scripts. This constraint diminishes the overall efficacy and scalability of these models in areas with varied linguistic contexts. In multilingual settings, where counterfeiters may leverage linguistic variances to produce counterfeit currency, such models encounter difficulties in adapting to novel or unfamiliar scripts, thus undermining detection accuracy. Future developments should concentrate on creating multilingual models that can identify and analyse many linguistic cues, hence enhancing the robustness and inclusivity of counterfeit detection.

Proposed Model Enhancements

Incorporating multilingual features and augmenting dataset variety are crucial measures for strengthening the resilience and flexibility of currency authentication algorithms. By integrating a broader spectrum of languages and regional dialects, these models can proficiently manage currencies from various linguistic origins, guaranteeing that security elements such as text, symbols, and watermarks are precisely processed irrespective of the language employed. Augmenting the dataset with diverse photos from various geographical regions and money types would enhance model performance, rendering it more adaptable and relevant in global situations.

Furthermore, the incorporation of transfer learning may substantially improve real-time detection abilities, especially for visually impaired individuals. Transfer learning, through the fine-tuning of pre- trained models, facilitates the development of a system that is both efficient and accessible. The system could offer auditory or tactile feedback to verify cash validity for visually impaired users, promoting enhanced inclusivity. This method enhances counterfeit detection and facilitates wider applicability in many cultural scenarios.

3. DISCUSSION

Evaluation of Deep Learning Techniques

The examined literature indicates that CNN-based models (Convolutional Neural Networks) provide considerable benefits compared to conventional methods in counterfeit currency detection. These models are proficient in recognising complex patterns and nuanced details in money photos, including microtext, watermarks, and security threads, which frequently pose difficulties for human detection or traditional machine learning methods [11]. Convolutional Neural Networks (CNNs) efficiently analyse high-dimensional image data, facilitating enhanced feature extraction and classification precision [3].

Moreover, classifiers such as Random Forest and ResNet-50 have exhibited superior efficacy in currency authentication endeavours. Random Forest offers resilience and precision through ensemble learning, but ResNet-50 excels at extracting intricate features owing to its deep architecture. Both classifiers necessitate substantial computational resources, encompassing extensive memory and processing capacity, to manage massive datasets and intricate models. This requirement may provide a constraint in low-resource settings, when access to high-performance technology could be limited. Although these models exhibit high accuracy, they require additional optimisation to guarantee scalability in resource-limited environments.

Practical Applications and Social Implications

Incorporating advanced deep learning technology into banking and public transaction systems has substantial potential to markedly diminish the circulation of counterfeit cash. By integrating advanced counterfeit detection models, including CNN-based and transfer learning systems, into ATMs, point-of-sale terminals, and other financial infrastructures, banks and financial institutions can more effectively identify counterfeit currency during transactions. This proactive strategy would mitigate the proliferation of counterfeit cash, hence enhancing security and confidence in the financial system.

The incorporation of mobile-based cash identification via deep learning models is a promising alternative for financial autonomy and security for visually impaired individuals. Mobile applications utilising deep learning algorithms could enable visually challenged individuals to scan money notes with their smartphones, providing auditory feedback or vibration warnings to verify the authenticity of the note. This technology would enable visually impaired individuals to autonomously manage financial transactions, facilitating their integration into the digital economy and enhancing their overall quality of life.

Future Directions

Areas for future research include:

To improve the efficacy of currency authentication systems, several critical areas require advancement:

Support for Multilingual Features: A significant drawback of existing currency detection methods is their incapacity to process multilingual currencies. Numerous nations possess currencies that incorporate numerous languages or scripts, exemplified by India's rupee, which features Hindi, English, and various regional languages. Enhancing model adaptability to include these multilingual elements will guarantee that counterfeit detection systems can effectively process and validate notes in multiple languages. This entails training models to identify text, symbols, and security aspects across many scripts, hence enhancing accuracy in numerous linguistic situations.

Low-Power and Embedded Systems: Numerous contemporary deep learning models necessitate substantial processing resources, rendering them impractical for implementation on mobile or resource- constrained devices. Creating lightweight models tailored for mobile and embedded systems would enable efficient currency detection on cellphones, ATMs, and other portable devices without sacrificing performance. Methods such as model pruning, quantisation, and distillation can reduce model size and computational requirements, facilitating real-time currency verification on resource-constrained devices.

Enhanced Data Augmentation: To augment model robustness, the integration of different and comprehensive datasets is required. Data augmentation techniques, like rotation, cropping, and scaling of photos, can generate synthetic versions of currency notes, enhancing the model's capacity to generalise across diverse settings, such as varying printing styles, lighting scenarios, or degradation of the currency. Augmenting the dataset to incorporate currencies from diverse nations, each with distinct characteristics and security measures, would enhance the system's resilience and adaptability, enabling it to manage a broad spectrum of real-world situations.

These solutions would enhance money authentication systems, rendering them more inclusive, efficient, and adaptable across many situations, thereby aiding in the global fight against counterfeit currency.

4. CONCLUSION

This review examines the increasing significance of deep learning models, including Convolutional Neural Networks (CNN) and ResNet-50, in improving the precision and dependability of currency authentication systems. These models have shown considerable effectiveness in identifying counterfeit currency by examining and interpreting complex patterns in currency photos. Convolutional Neural Networks (CNNs) excel at recognising hierarchical characteristics, ranging from basic edges to intricate patterns, making them particularly adept at identifying subtle security elements such as microtext, watermarks, and security threads. Likewise, ResNet-50, utilising its deep residual network design, excels in feature extraction, especially in identifying intricate elements in money notes. The capacity to identify diverse characteristics renders CNN and ResNet-50 very advantageous for currency verification jobs, distinguishing them from conventional approaches that frequently depend on manual examination of observable security factors.

A notable problem is the computational requirements imposed by these deep learning models, especially for intricate tasks such as counterfeit detection. Models such as CNN and ResNet-50 necessitate considerable computational power and memory, which may pose constraints in regions with inadequate technical infrastructure or for devices with limited processing capabilities. The substantial computing demands hinder mobile devices and embedded systems from effectively managing real-time money authentication. Researchers must concentrate on creating lightweight models that preserve high accuracy while diminishing the computing load. Techniques such as model pruning, quantisation, and distillation can reduce model size and enhance optimisation for low-power mobile and embedded systems, therefore facilitating currency authentication in resource-constrained settlements.

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