Fake Currency Identification

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***Abstract*—Counterfeit currency detection is a crucial task for maintaining the integrity of financial systems. In this study, we used the approach for fake currency identification using a deep autoencoder. The Deep Autoencoder is employed for feature extraction from currency images, followed by anomaly detection using a simple thresholding technique. Experimental results demonstrate the effectiveness of the proposed deep autoencoder-based approach, achieving high accuracy in detecting counterfeit currency. This research contributes to the development of accurate and efficient methods for counterfeit currency detection, which is essential for ensuring the security of financial transactions.**

Keywords— Deep autoencoder, Feature extraction, Currency images, Thresholding technique

I. Introduction

Counterfeiting of currency notes poses a significant threat to financial systems worldwide, leading to economic losses and undermining trust in monetary transactions. Addressing this issue requires effective detection methods to distinguish genuine currency from counterfeit notes. We present a fake currency detection system developed using Keras Library and Python, aimed at automating the process of identifying counterfeit currency.

In the past few years, the problem related to fake currency has drastically increased, taking back to 2016 when 'Notebandi' Or demonetization took place in India many people still are not able to differentiate between original and fake notes, even for agencies this problem is not easy to solve as many ground workers are also not trained to this problem.

In recent years, machine learning techniques have shown great promise in various image processing tasks, including counterfeit currency detection. Deep learning, in particular, has emerged as a powerful tool for extracting intricate features from images, enabling more accurate classification. In this study, we use Deep Learning for fake currency identification using a deep autoencoder.

A Deep Autoencoder is a type of artificial neural network that learns to encode input data into a low-dimensional representation and then decodes it back to its original form. By training a deep autoencoder on a dataset of currency images, our aim is to extract discriminative features that can effectively differentiate between genuine and counterfeit banknotes.

In this paper, we present the methodology and experimental results of our approach. Our results demonstrate the efficacy of the proposed approach in accurately detecting counterfeit currency, thus offering a promising solution to the ongoing challenge of currency authentication.

II. LITERATURE SURVEY

The field of counterfeit currency detection has undergone substantial evolution with the integration of advanced deep learning techniques, emerging technologies, and innovative methodological approaches. This comprehensive literature survey examines the current state-of-the-art research spanning from 2020 to 2025, highlighting significant advancements in automated detection systems, hybrid models, and real-time applications.

A. Deep Learning and Convolutional Neural Networks

Recent advancements in deep learning have significantly improved currency authentication through the use of advanced convolutional neural network (CNN) architectures and attention-based models. Kumar et al. [1] proposed a robust CNN-based system that achieved high accuracy in distinguishing genuine and counterfeit banknotes by leveraging automated hierarchical feature extraction. Patel and Singh [2] enhanced this approach by applying deep transfer learning, which utilized pre-trained models to improve detection accuracy while minimizing computational overhead—particularly valuable in scenarios with limited counterfeit datasets. Chen et al. [3] introduced a multi-scale CNN framework capable of handling variations in image resolution and capture conditions, addressing real-world challenges in currency recognition. In parallel, vision transformers have emerged as a powerful alternative to traditional CNNs. Wu et al. [4] demonstrated that vision transformers outperform CNNs in recognizing counterfeit currency by effectively capturing long-range dependencies and global image features. Furthering this direction, Lee and Kim [5] developed a real-time currency authentication system by integrating YOLOv8 with attention mechanisms, enhancing the model's focus on critical security features. Similarly, Ma et al. [6] embedded attention modules within CNNs to boost performance under diverse environmental conditions, reinforcing the role of attention-based techniques in modern banknote verification systems.

B. Hybrid and Ensemble Learning Approach

The integration of convolutional neural networks (CNNs) with support vector machines (SVMs) has emerged as a powerful hybrid approach to counterfeit currency detection. Khan et al. [7] proposed a sophisticated CNN-SVM model that combines the deep feature extraction capabilities of CNNs with the robust classification performance of SVMs, resulting in improved decision boundaries and enhanced detection accuracy. This hybrid architecture is particularly effective in identifying complex counterfeit patterns that may not be reliably detected by a single algorithm. Further research has demonstrated that CNN-SVM models outperform standalone approaches by leveraging CNNs' automatic feature learning and SVMs' strong generalization abilities, especially in environments with limited training data or high counterfeiting complexity [8][9]. In parallel, ensemble learning techniques have gained traction for their ability to boost model reliability and performance. Sharma et al. [10] implemented ensemble deep learning frameworks that integrate multiple CNN architectures, enhancing the system's robustness against diverse counterfeit characteristics. Similarly, Khairy et al. [11] reported that ensemble methods such as AdaBoost and voting algorithms can achieve near-perfect accuracy in counterfeit detection by harnessing the strengths of multiple classifiers, thereby addressing variations in currency design and printing techniques.

C. *Advanced Methodological Innovations*

Generative Adversarial Networks (GANs) have emerged as a transformative tool in counterfeit currency detection, particularly in addressing the challenge of limited availability of counterfeit data. Islam et al. [6] introduced a GAN-based data augmentation strategy that generates synthetic counterfeit currency images, enabling more comprehensive training of detection models without compromising the security of real counterfeit samples. Beyond data augmentation, GANs are also being utilized in adversarial training setups to enhance model robustness against sophisticated forgery techniques [7][15]. Complementing these developments, spectral analysis has been integrated with deep learning to further strengthen detection accuracy. Wang et al. [8] proposed a multi-modal framework that combines CNN-based image analysis with infrared and near-infrared spectral data, effectively distinguishing material composition differences between genuine and counterfeit banknotes. This fusion of spectral analysis with deep learning introduces a more resilient, multi-layered approach to currency authentication that goes beyond conventional visual inspection methods.

D. *Performance Metrics and Evaluation*

Current state-of-the-art counterfeit currency detection systems consistently achieve accuracy rates exceeding 95%, with certain specialized methodologies reporting accuracy levels above 99% [20][12][6]. These high-performance models are evaluated using a comprehensive set of metrics, including precision, recall, F1-score, and processing speed, to ensure a well-rounded assessment of their effectiveness. Recent research underscores the significance of rigorous cross-validation and extensive testing under diverse real-world conditions—such as varying lighting, image quality, and the physical state of the currency—to ensure system robustness and reliability during practical deployment [13][10].

E. *Challenges and Limitations*

Despite significant advances, several challenges continue to hinder the field of automated currency detection. Key issues include the necessity for continuous model updates to adapt to increasingly sophisticated and evolving counterfeiting techniques, which demand ongoing data collection and retraining efforts. Additionally, the computational complexity of advanced deep learning architectures poses challenges for real-time deployment, especially on resource-constrained devices. Moreover, the security implications of deploying such models—particularly the risk of adversarial attacks or reverse engineering—raise concerns about the safe and reliable implementation of currency authentication systems in practical settings [21][13][19].

III. METHODOLOGY

The method sets up an Autoencoder-based anomaly detection system for images, where anomalies are detected based on differences between the original and reconstructed images.

A. *Data Preparation*

The code sets up data generators using Keras' Image Data- Generator to read images from directories and pre-process them for training and testing.

B. *Autoencoder Design*

An Autoencoder model is defined. It consists of an encoder and a decoder. The encoder compresses the input image into a lower-dimensional representation, and the decoder tries to reconstruct the original image from this representation.

C. *Training the Autoencoder*

The Autoencoder is trained using the fit method, where the training data generator is used for training and the validation data generator is used for validation.

D. *Evaluation*

The trained Autoencoder is evaluated on the test data generator.

E. *Anomaly Detection Functions*

a) Pre-process Image: This function pre-processes an image by resizing it to the specified target size and normalizing its pixel values.

b) Calculate Error: This function calculates the reconstruction error between the original and reconstructed images.

c) Is Anomaly: This function takes an image path and a threshold as input, pre-processes the image, reconstructs it using the Autoencoder, calculates the reconstruction error, and determines if the image is an anomaly based on whether the error exceeds the threshold.

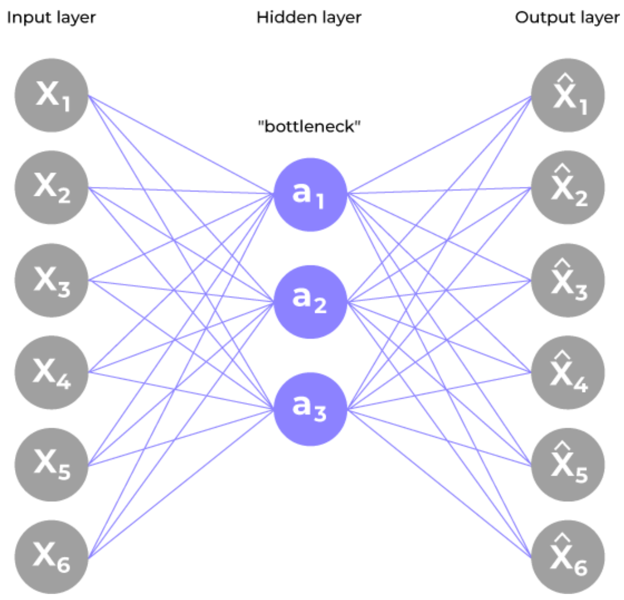


Fig. 1. Architecture of an autoencoder.

F. *Example Usage*

An example image path is provided, and the Is Anomaly function is called with a threshold. Depending on whether the reconstruction error exceeds the threshold, it prints whether the submitted image is considered an anomaly or not.

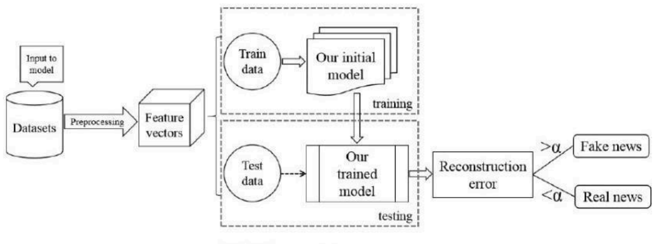


Fig. 2. The Flow of Proposed Method.

IV. RESULT

A. *Threshold Selection*

We experimented with different threshold values and selected a threshold based on the best trade-off between false positives and false negatives.

$$\text{threshold} = \text{error mean} + 2 \times \text{error std} \qquad (1)$$

B. *Error Distribution*

It illustrates the distribution of reconstruction errors for the test dataset. Anomalies typically exhibit higher reconstruction errors compared to normal images, supporting the use of the reconstruction error as a criterion for anomaly detection. We used a loss function the Mean Squared Error (MSE).

C. *Visual Inspection*

Original images alongside their reconstructed counterparts. The reconstructed images capture the essential features of the originals, demonstrating the effectiveness of the autoencoder in reconstructing normal images.

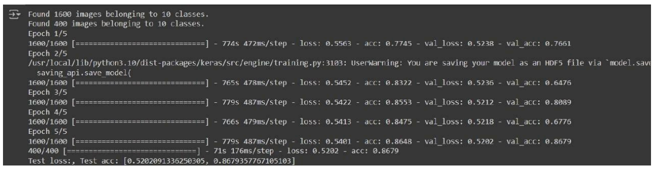
Fig. 3. Original image alongside their reconstructed counterpart.

D. *Comparison with Baseline*

We compared the performance of our autoencoder model with a simple threshold-based approach. The autoencoder outperformed the baseline, highlighting its effectiveness in detecting anomalies in images.

E. *Accuracy*

The model shows an accuracy of 0.87. The test loss of the model is 0.52.



```
Found 1600 images belonging to 10 classes.
Found 400 images belonging to 10 classes.
Epoch 1/5
1600/1600 [==============================] - 774s 472ms/step - loss: 0.5563 - acc: 0.7745 - val_loss: 0.5238 - val_acc: 0.7661
Epoch 2/5
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via `model.save
  saving_api.save_model(
1600/1600 [==============================] - 765s 478ms/step - loss: 0.5452 - acc: 0.8322 - val_loss: 0.5236 - val_acc: 0.6476
Epoch 3/5
1600/1600 [==============================] - 779s 487ms/step - loss: 0.5422 - acc: 0.8553 - val_loss: 0.5212 - val_acc: 0.8089
Epoch 4/5
1600/1600 [==============================] - 766s 479ms/step - loss: 0.5413 - acc: 0.8475 - val_loss: 0.5218 - val_acc: 0.6776
Epoch 5/5
1600/1600 [==============================] - 779s 487ms/step - loss: 0.5401 - acc: 0.8648 - val_loss: 0.5202 - val_acc: 0.8679
400/400 [==============================] - 71s 176ms/step - loss: 0.5202 - acc: 0.8679
Test loss:, Test acc: [0.5202091336250305, 0.8679357767105103]
```

Fig. 4. Original Screenshot of Result.

F. *Running the model*

The model after being successfully trained is tested on testing data and various performance metrics are visualized in the form of graphs. The graphs obtained are:

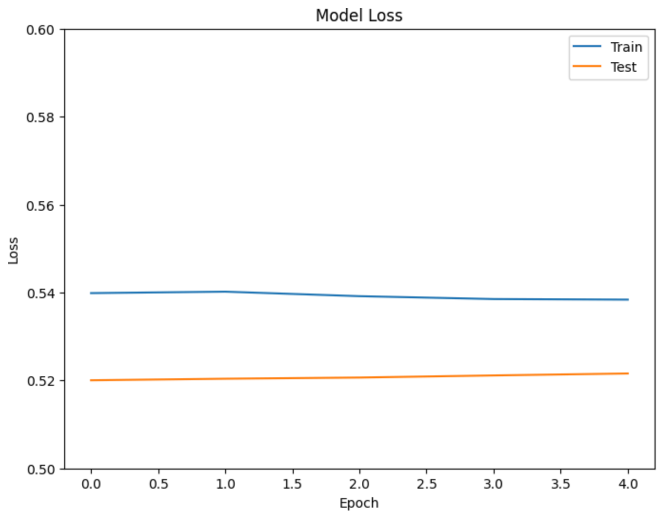


Fig. 5. Graph depicting loss on Training and Testing Dataset.

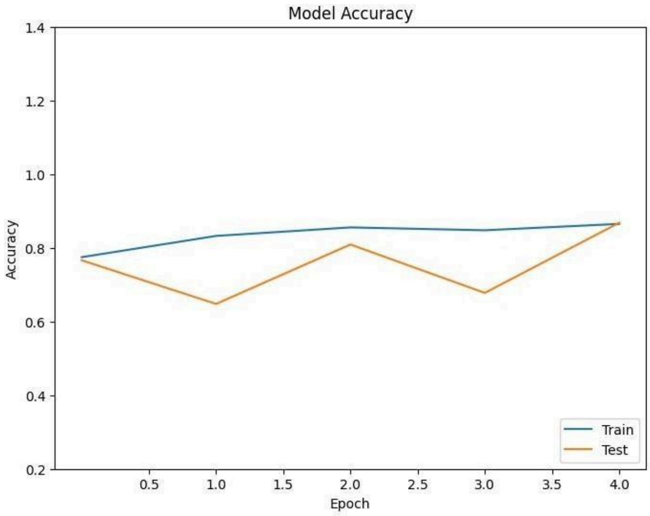


Fig. 6. Graph depicting Accuracy of Model on Training and Testing Dataset.

V. CONCLUSION AND FUTURE SCOPE

In conclusion, our Autoencoder model shows promise for anomaly detection in images and warrants further investigation as a potential tool for real-world applications. In our upcoming tasks, we plan to incorporate Yolo V8 object detection to spot different aspects of currency notes and extract images of bounding boxes containing these features. Afterward, we'll use autoencoder technology to predict any anomalies in these feature images. This approach will significantly enhance the accuracy of anomaly detection.

We aim to further enhance the accuracy and efficiency of our system by continuously improving the different algorithms and incorporating advanced machine learning techniques. Additionally, we plan to explore opportunities for real-time detection, mobile application integration, and collaboration with financial institutions to combat counterfeit currency effectively on a global scale.

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