JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Comparative Analysis of Machine Learning Models to Identify Fake Currency

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Abstract: As counterfeit currency techniques become more sophisticated, advanced detection methods that adapt accurately are necessary. This study investigates the application of three key machine learning algorithms—K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Convolutional Neural Networks (CNN)—to detect fake Indian currency notes using an image-based dataset. The SVM showed outstanding results with a perfect test accuracy of 1.00, while the KNN achieved a commendable accuracy of 0.92. The CNN, however, had lower accuracy at 0.76, underscoring challenges in feature learning and generalization. These findings suggest that traditional machine learning models like the SVM are highly effective for structured detection tasks. In contrast, CNNs might require additional adjustments and data enhancements to perform equally well. This study highlights the significant role of machine learning in combating economic crimes such as currency counterfeiting. It sets the stage for further development of more effective detection systems.

***Keywords* - Classification Algorithms, Convolutional Neural Networks, Counterfeit Currency Detection, K-Nearest Neighbors, Machine Learning, Support Vector Machine.**

I. Introduction

Currency acts as a means of transaction for products and offerings, typically distributed by governments and accepted for payments at face value [1]. A currency note refers to a designated quantity of paper money in a particular currency [2]. Counterfeit currency involves illegally fabricating money by criminals aiming to replicate authentic government-issued notes, using high-tech methods to produce deceptive replicas for transactions or economic disruption [3]. Counterfeit currency represents a significant risk in today's globalized environment, with criminals continuously devising new methods to mimic currency, thus endangering financial systems and affecting economic stability. During the 2021-22 period, the Reserve Bank of India (RBI) identified 6.9% of Fake Indian Currency Notes (FICN), while other banking institutions detected the other 93.1%, leading to problems such as currency depreciation, economic instability, and inflation [4, 5].

Globally, financial institutions face a formidable challenge in detecting counterfeit currency, further complicated by advanced printing technologies that enhance the quality of forged notes, making them more challenging to recognize. In India, various strategies are employed to authenticate currency notes. The RBI has embedded several security features in banknotes, including watermarks, optically variable ink, security threads, and latent images to combat counterfeiting [6]. UV and IR detection is also essential for identifying fake Indian currency [7]. Technological advancements continue to improve the methods of validating currency and combating financial crimes. Machine learning, supported by computer vision, is vital in verifying genuine Indian currency [8]. Through image processing, this technology detects anomalies in currency images to identify counterfeits. Machine learning differentiates between authentic and counterfeit notes by utilizing data-driven algorithms.

This study explores three distinct machine learning models— KNN, SVM, and CNN— each offering unique benefits for image-based classification tasks. The aim is to assess and compare the performance of these models in detecting counterfeit currency using an image dataset comprising both genuine and fake Indian currency. These models were selected due to their suitability and effectiveness in image recognition tasks pivotal in spotting subtle differences between real and fake notes, which are often not apparent to the naked eye.

II. Literature Review

Recent research efforts have been robust in the field of counterfeit banknote detection.

Jadhav et al. analyzed banknotes from multiple countries using deep learning for detailed feature extraction and analysis. They devised a system using a deep learning algorithm to identify counterfeit banknotes via general scanners to reduce personal financial losses [9]. Nayak applied convolution-based deep neural networks to analyze currency images, training the system with a dataset of two thousand notes to detect counterfeit money effectively in real time [10]. Kamble et al. developed a CNN model to detect fake notes using mobile devices, with promising results from their custom dataset indicating the potential for future enhancements in deep CNN architectures [11]. Laavanya and Vijayaraghavan used deep CNN to inspect currency images, employing a transfer-learned CNN trained on Indian currency notes for the adept real-time detection of counterfeits [12]. Sharma et al. utilized deep CNNs, specifically a Deep VGG16 model, trained on datasets of genuine and counterfeit Indian banknotes, achieving an impressive accuracy of over 99% in identifying fake notes, thereby providing a reliable detection tool [13]. Zhang and Yan utilized the Single Shot MultiBox Detector (SSD) along with CNN techniques to improve the extraction of features from paper currency, which substantially increased the average recognition accuracy to 96.6% [14].

Pachón et al. investigated various CNN architectures for transfer learning, identifying the most effective points to freeze the learning process. They created a tailored model inspired by AlexNet's sequential CNN format, achieving peak accuracy with a ResNet18 model at 100% [15]. Meanwhile, Pham et al. developed a new method for classifying banknotes as genuine or counterfeit using visible-light images captured by smartphones, employing CNNs to outperform previous approaches in recognizing fake currency from various countries [16].

Ali et al. created DeepMoney, a system utilizing Generative Adversarial Networks (GANs) to distinguish between fake and real Pakistani banknotes, combining unsupervised and supervised learning to achieve 80% accuracy [17]. Khairy et al. explored ensemble learning algorithms, specifically AdaBoost and voting ensembles, to enhance the accuracy of detecting counterfeit banknotes, achieving accuracy up to 100% [18].

This body of work underscores the significant progress in utilizing deep learning and CNN for counterfeit currency detection, demonstrating high accuracy and potential for application across various platforms and techniques. However, comparative analyses involving KNN, CNN, and SVM in this context remain unexplored. This study seeks to bridge this gap in the existing literature.

III. Medhodology

The methodology section outline the plan and method that how the study is conducted. This includes Universe of the study, sample of the study,Data and Sources of Data, study's variables and analytical framework. The detailsare as follows;

3.1 Dataset Description

This research employed the Indian Currency Dataset, accessible on Kaggle, and features color images of authentic and counterfeit Indian banknotes. The dataset is divided into two principal sections: a training set and a testing set, with each set containing subfolders labeled 'real' and 'fake' to denote authentic and counterfeit notes, respectively. The training set includes 120 authentic and 125 fake images, while the testing set comprises 48 authentic and 59 fake images. These images depict banknotes of different denominations and states of wear, offering a varied foundation for developing and assessing machine learning models.

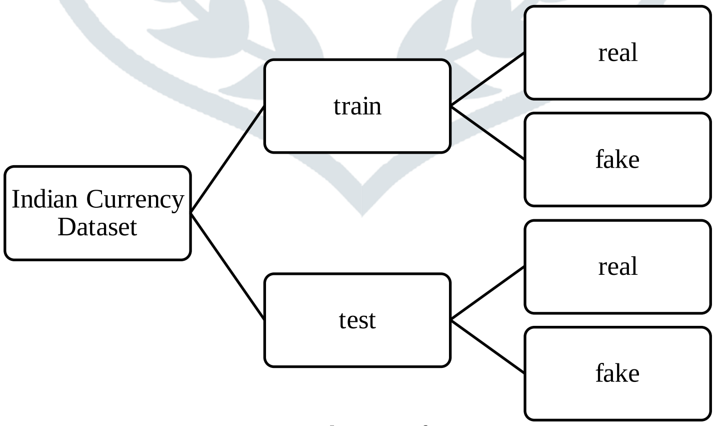

Fig 1: Distribution of Dataset

3.2 System Design

3.2.1 Data Preprocessing

The raw images were processed through several steps to enhance model efficacy:

- Grayscale Conversion: Images were converted to grayscale for the KNN and SVM algorithms to simplify processing demands and concentrate on textural and shape details rather than color.
- Image Resizing: Images were adjusted to uniform sizes; for KNN and SVM, they were resized to 64×64 pixels, while for CNN, the size was set at 150×150 pixels to preserve more information.
- Normalization: The pixel values were normalized to a scale from 0 to 1, aiding in more efficient model training and convergence.
- Data Augmentation: For the CNN, techniques like rotation, width and height adjustments, shear transformations, zoom operations, and horizontal flips were used to improve the model's resilience and reduce the risk of overfitting.

3.3 Model Development

Three distinct machine-learning algorithms were used to identify whether currency notes were genuine or counterfeit:

- KNN: This approach utilized a KNN classifier with k=3, which determines each test image's classification based on the majority rule among its three closest neighbors in the feature space.
- SVM: Employing an SVM with a linear kernel, this model identifies the optimal hyperplane that distinguishes between authentic and counterfeit notes in the feature space.
- CNN: This architecture is structured sequentially and features four convolutional layers, each succeeding by a max-pooling layer. The configuration ends with two dense layers. Dropout layers are also included to reduce overfitting.

3.4 Training

The models underwent training with specific setups:

- KNN and SVM: These models were trained on flattened grayscale images for the KNN and standardized feature vectors for the SVM.
- CNN: The CNN was trained for 15 epochs using a batch size of 20, and part of the training dataset was set aside as a validation split to optimize parameters and prevent overfitting.

3.4.1 Evaluation Metrics

The effectiveness of the models was gauged using several metrics:

- Accuracy: This metric evaluates the overall performance of the model.
- Confusion Matrix: A confusion matrix visually represents each model's performance by comparing actual and predicted classifications.
- Precision and Recall: These metrics assess the model's ability to identify counterfeit notes and reduce false negatives correctly.
- F1-Score: Used as a balanced mean of precision and recall, this score is instrumental in situations where the distribution of classes is uneven.

IV. RESULTS AND DISCUSSION

The assessment of three distinct algorithms— KNN, SVM, and CNN— for identifying fake currency notes reveals differences in performance, which are influenced by their architecture and the preprocessing techniques applied.

4.1 Result

Model	Accuracy	Precision	Recall	F1-Score
KNN	0.925234	0.857143	1.0	0.923077
SVM	1.000000	1.000000	1.0	1.000000
CNN	0.766355	0.657534	1.0	0.793388

Table 4.1: Model Performance Summary

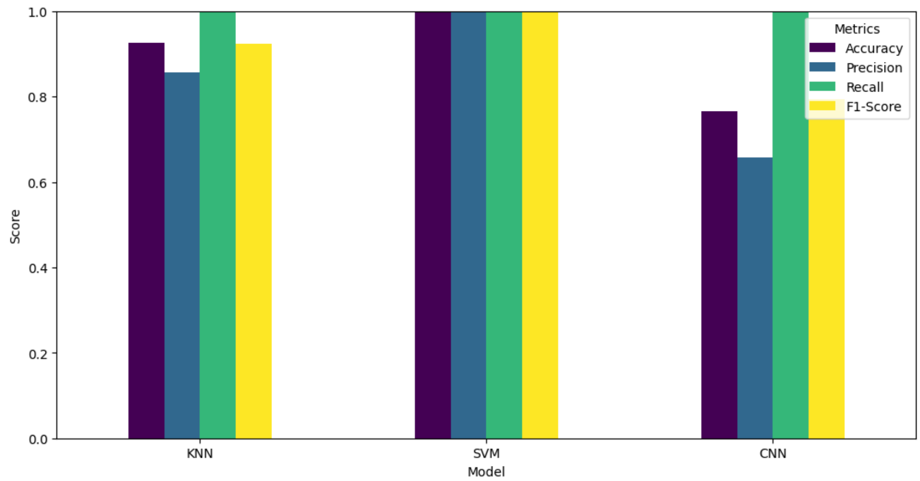

Fig 2: Evaluation Metrics Comparison between KNN, SVM, and CNN

Fig 3: Confusion Matrix Comparison of KNN, SVM, and CNN

4.1.1 Analysis of SVM Performance

The SVM model demonstrated superior performance, achieving perfect scores across all metrics, including 100% accuracy, precision, and recall in the training and testing phases. This indicates that SVM's linear decision-making boundaries are exceptionally effective at differentiating between all real and fake notes without errors, emphasizing its capability to manage high-dimensional data and delineating categories based on the characteristics derived from the currency images. This high accuracy underscores the SVM's efficiency in handling linear separations in complex spaces.

4.1.2 Analysis of KNN Performance

The KNN model exhibited strong capabilities in classifying currency notes, achieving an accuracy of roughly 92.52% and flawless recall, effectively identifying every authentic note without mistakenly labeling it as counterfeit. Although highly effective, KNN did not match the perfect results of the SVM, primarily due to some genuine notes being incorrectly labeled as fake, which lowered its precision. The model's success is attributed to the problem's nature, where similar examples cluster closely in the feature space, fitting KNN's operational strengths. Initial challenges such as noise, irrelevant data, and high dimensionality issues were mitigated through preprocessing techniques like image resizing and converting to grayscale.

4.1.3 Analysis of CNN Performance

The CNN model achieved a 100% recall, successfully identifying every genuine banknote, but struggled with a low precision rate of 65.75%. This led to a reduced overall accuracy of 76.64%, mainly due to numerous counterfeit notes being misclassified as real. While the perfect recall rate shows CNN's proficiency in recognizing features in authentic notes, the poor precision highlights difficulties in accurately detecting features in counterfeit notes with the current setup. This outcome suggests possible challenges such as:

- Overfitting: Despite measures like data augmentation and dropout layers, the model's complexity may still be too high for the dataset's scale and complexity.
- Underfitting: Inadequate feature capture by the CNN might result from too few training epochs or less than optimal architectural decisions.
- Data Quality and Volume: Effective CNN performance typically requires substantial and diverse data sets. The dataset might not have been adequate in size or variety, affecting CNN's ability to generalize well on the test set.

4.2 Discussion

The comparative analysis of KNN, SVM, and CNN models in detecting counterfeit currency revealed distinct capabilities and challenges for each. SVM excelled, achieving 100% across all metrics. It showcased its reliability and effectiveness in managing high-dimensional data and establishing clear decision boundaries in image classifications. KNN showed strong recall, identifying all real notes accurately, which is crucial where missing a genuine note is not an option. However, its lower precision might lead to significant issues in cases of false positives. Meanwhile, despite its perfect recall, CNN struggled with precision and recorded the lowest overall accuracy. This indicates that while CNNs are adept at recognizing genuine notes, they need refinements to better generalize counterfeit features, potentially due to model overfitting, underfitting, or limited data diversity.

V. Conclusion and Future Work

This research showcased the effectiveness of various machine-learning approaches in identifying counterfeit currency, comparing the performances of KNN, SVM, and CNN. The SVM excelled with perfect accuracy, proving its discriminative solid power for this specific dataset, whereas KNN also showed commendable performance. On the other hand, CNN was less effective, indicating opportunities for improvement. These results reinforce the potential of machine learning as a potent tool for augmenting currency verification processes.

Future research should aim to enhance the CNN model by exploring different architectures, deeper networks, or more sophisticated image-processing methods to improve feature extraction. Expanding the dataset to include a broader variety of currency types could also aid in developing more universally applicable models. Investigating ensemble methods that leverage the strengths of multiple models might also offer a way to boost accuracy and robustness in real-world applications.

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