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Detection of Fake Currency Using Machine Learning Models

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***Abstract:** The goal of this research is to determine whether a given cash sample is genuine or counterfeit. Based on the colours, widths, and serial numbers described, several conventional procedures and methods exist for identifying counterfeit cash. Image processing proposes a number of machine learning techniques with a false-identity detection success rate of 99.9 percent for paper cash in today's era of modern computing. In algorithm-based techniques for detection and identification, various entities such as color, form, paper width, and image filtering on the note play a crucial role. This research proposes the application of K-Nearest Neighbors (KNN) followed by image processing as an effective method for spotting counterfeit money. KNN is favored for use in computer vision problems due to its outstanding accuracy, particularly when dealing with small datasets. This approach leverages the strengths of KNN in handling limited data to enhance the precision and reliability of counterfeit money detection. The accurate facts and information on entities and attributes associated to currency have been compiled in this banknote authentication dataset, which was developed using advanced computational and mathematical methodologies. AI calculations and picture handling are utilized for information handling and information extraction to accomplish an elevated degree of exactness and accuracy.*

***Keywords:** Fake Currency Detection, SVM, CNN, KNN.*

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1. INTRODUCTION

Many individuals engage in criminal behaviour in this century because most of them understand how technology works. One such activity is the creation of counterfeit cash with the express purpose of deceiving others. This proposal seeks to address this unlawful practise by offering a potential remedy. There were 132 reported incidents of counterfeit cash in 2018, and 181 reported incidents so far in 2019 in India, a 37 percent increase over 2018. In Order to curb this fraudulent conduct, a system is developed that can be implemented into electronic devices that will identify the false note as soon as it is scanned by the device. KNN, a tried-and-true method, is among those under consideration; it will be employed in the suggested system to achieve higher precision. In order to classify a new data point, the K-nearest neighbours (KNN) method first saves all of the existing data and then uses similarity to make a determination. This implies that the KNN method may be utilized to rapidly and precisely sort recently arising information into a reasonable suite classification. The most used distance metric is the Euclidean one. Next, it determines which of the point's k closest neighbours also belong to the same class.

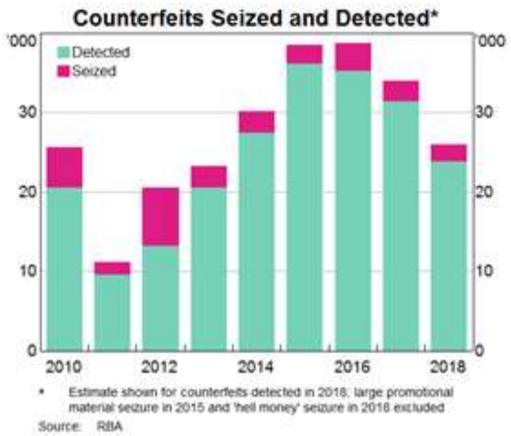

Fig.1 Counterfeits Detected

In k-NN, the central computation involves the online 'searching' for the k closest neighbors of a given testing case, eliminating the need for an offline training step. The 1-NN (nearest neighbor) method is frequently employed as a benchmark for other classifiers. It is valued for its ability to yield strong classification performances in numerous pattern classification scenarios. Despite the potential variation in classification outcomes when using different k values, 1-NN remains a reliable reference for evaluating and comparing classifier performance. Euclidean distance is determined by the following function:

$$dist\,(A,B) = \sqrt{\frac{\sum_{i=1}^{m}(x_i - y_i)^2}{m}}$$

Fig.2 Euclidean formula

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Some flaws and shortcomings were noticed in this direct approach, which prevented the system and false identification technique from functioning more effectively.

- ✓ a blurring of movement issue,
- ✓ Image capture device-induced noise
- ✓ A less-effective method for extracting features.

As a result of these widespread issues, the notion of using pictures for processing purposes was established, which cleans up the entities included in images (such as their shape, colour, and serial numbers) to provide more differentiation and efficiency. Due to the modest size of the data set, the KNN method is well suited to the system, and good results on the performance metrics are to be anticipated. A counterfeit currency detection system serves a dual purpose by not only restricting the circulation of counterfeit money but also providing incentives for dealers to accept or make payments in cash. This system acts as a deterrent, discouraging individuals from circulating fake notes, and contributes to maintaining an appropriate flow of currency within the economy. By ensuring the integrity of the currency in circulation, it fosters trust in financial transactions and supports a healthy economic environment.

Literature Survey

In the past, people have conducted several forms of research and study. There were a variety of improvements and developments noted. Data for false note identification has already been gathered using professional cameras, with fair to high accuracy shown thanks to very straightforward machine learning techniques. Historically, K closest neighbour algorithms were employed to detect forgeries in currency. As data sizes grew, the systems' performance deteriorated. After that framework ran over to order the exactness and acknowledgment rate with some improvement in AI calculations and profound learning standards. The high and huge informational indexes were causing informationdistortion, and the 98% accuracy wasn't helping much. Previously, these detections were only done using open cv and python, but with the advent of new deep learning approaches, a total of 100 photos per denomination were gathered and analysed. There was a comparison of the accuracy of the training and testing sets. This results in a greater value for the elongating chain type efficiency than is possible with other methods. The system relied on the principle of transfer learning. The capturing of the noise was yet another issue that called for further improvement. From that point onward, a Convolutional brain network went into the estimation for the blunder expulsion. Both preparation misfortune (TL) and approval misfortune (VL) propensities were analyzed. Customarily, preparing exactness (TA) was utilized to analyze precision designs. Successful AI, Profound convolutional brain organization, and resulting picture handlingtechniques are used to detect counterfeit notes in 2021. Its effectiveness is now at its highest level.

Proposed System

The graphic below depicts the process flow of our suggested system.

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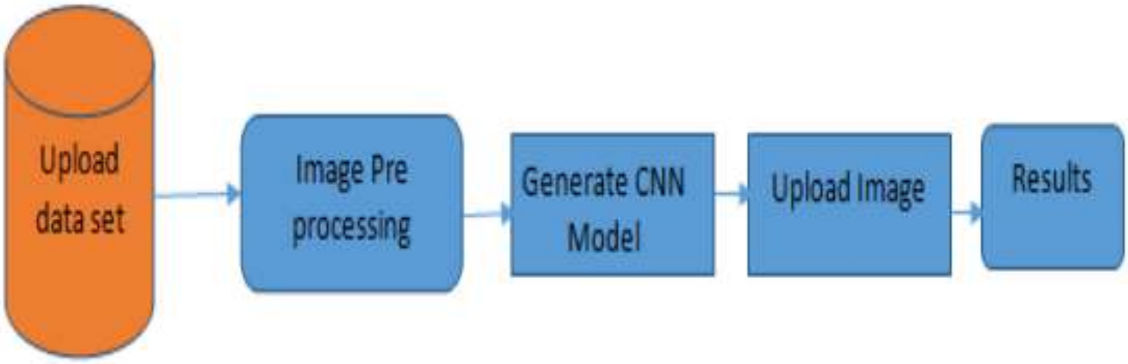

Fig. 3: System Workflow

Implementation Modules
Dataset
The informational collection was created by catching top notch photos of both genuine and fake money utilizing a modern camera. The pictures are 400 pixels on a side. The lens employed and the depth of field meant that the resulting grayscale images were only 660dpi. Wavelet Transform was performed to analyse these photos and determine key characteristics.

Preprocessing
The first four characteristics—"variance," "skewness," "kurtosis," and "entropy"—were used as independent or input variables in this module, while "class" served as the dependent or output variable. After data is normalised and preprocessed, it is then partitioned. We partitioned the information using the Kfold feature of sklearn.model_selection. The goal of utilising this library is it assists with securing a more precise handle of the calculation.

Building Model
The sklearn library was used to bring in the necessary classifiers for this project. We developed a procedure that, given the algorithm, training data, and testing data as inputs, would produce a model that had been trained and had its performance measured. This process was done for each fold, and the totals from each pass were compiled into a single list. In conclusion, the cross-approval foresee module is utilized to develop a disarray framework for every one of the strategies.

Performance Evaluation
In order to ensure that the model is accurate, performance metrics are utilised. The f-score, together with accuracy and precision, are used to evaluate the success of this project. Diagrams were drawn for every presentation metric and thought about the outcomes. For this assignment, we utilize the k-overlap cross-approval strategy.

Implementation Algorithms
Support Vector Machine
In the realm of data analysis for classification and regression, support-vector machines (SVMs), occasionally referred to as support-vector networks, stand as supervised learning

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models equipped with corresponding learning algorithms.Non-probabilistic binary linear classifiers are what the SVM training algorithm creates in order to classify fresh instances.

KNN

Within the spectrum of Supervised Learning-based Machine Learning algorithms, K-Nearest Neighbor stands out as one of the simplest. The K-Nearest Neighbors (K-NN) method classifies new instances or data based on their perceived similarity to previously classified data points. This algorithm utilizes all available data to determine the appropriate category for a new data point. Consequently, the K-NN technique proves efficient in swiftly and accurately assigning newly emerging data into suitable categories. The K-NN method is versatile, since it can be used to both Regression and Classification issues.

2. RESULTS

In the wake of preparing the model utilizing the informational index and the strategies framed above, we tried them to perceive how they fared. We were able to get a feel for how each method fared by calculating the aforementioned performance metrics. The f-scores, accuracy, and precision for each algorithm are shown below.

Table 1: Precision in Comparing Algorithms

Algorithm	Accuracy	Precision	F1-Score
CNN	67.88%	65.08%	65.35%
SVM	75.91%	73.12%	71.85%
K NN	72.26%	75.05%	59.45%

Fig. 4: Dataset of either fictional or actual currency

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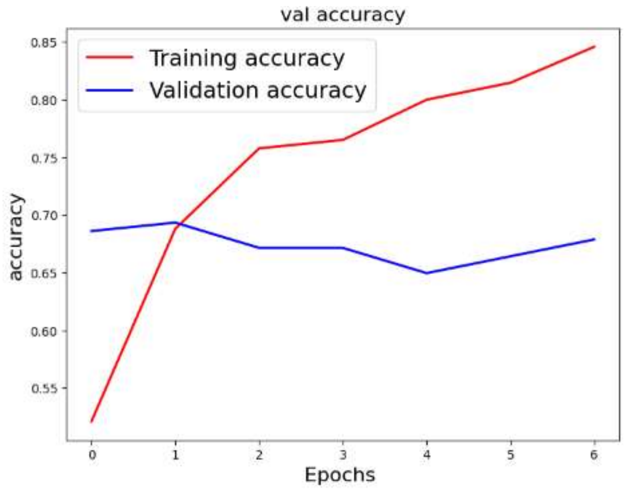

Fig. 5: CNN Model Validation During Training and Testing

Fig.6: The CNN Model Confusion Matrix

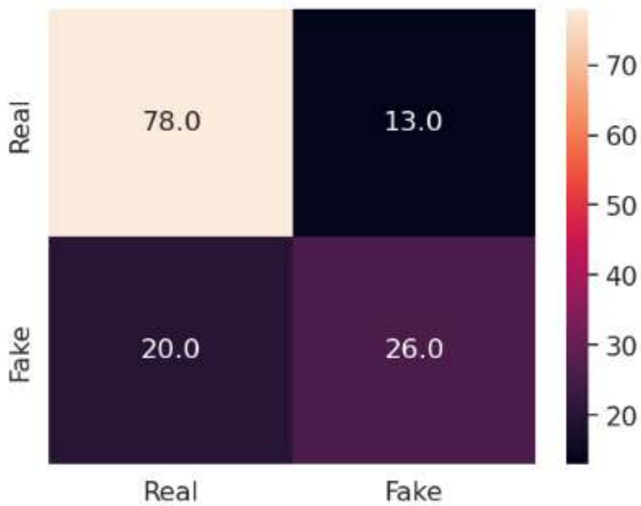

Fig. 7: Confusion Matrix for SVM Model

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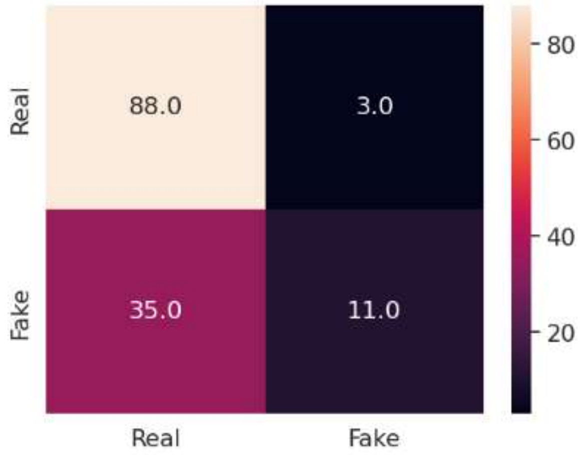

Fig. 8: K-Nearest Neighbour Model Confusion Matrix

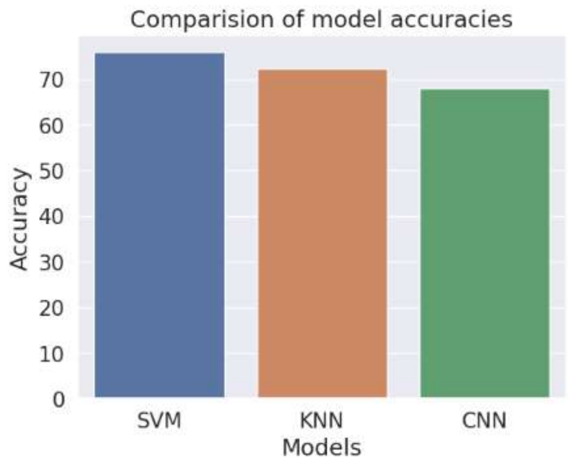

Fig. 9: Graph for Analysing Comparisons

3. CONCLUSION

In the wake of executing and dissecting the discoveries gained, we can confirm that every one of the three calculations utilized were amazingly exact at classifying notes as genuine and fake in view of the used informational index. However, as we saw above, KNN was superior than both of the other methods. Only two fake bills were mistakenly identified, for a total accuracy of 99.9%. The sample size was tiny, thus this finding should be interpreted with caution. Taking into account the real-world situation, its present performance may not hold up after considering all 1372 samples. We suggest expanding this into a much bigger data collection by include photographs of both genuine and counterfeit bills. The result will be a more accurate representation. Convolutional Neural Networks (CNNs) and other deep learning algorithms may be implemented with great accuracy in image processing situations when a big data set is available. Moreover, by utilizing CNN the undertaking may straightforwardly dissect photographs as information, and wavelet alteration won't be fundamental. Along these lines, utilizing the framework may become easier and more convenient. Additionally, since being used in monetary institutions is reasonable, consumers

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will appreciate the ease with which they can just take a photo and have it validated; this can be accomplished with the assistance of CNN as indicated above. Therefore, the following suggested actions may be taken to make the project more resilient and professional.

4. REFERENCES

1. D. V. Kapare, S. Lokhande, and S. Kale, "Automatic Cash Deposite Machine With CurrencyDetection Using Fluorescent And UV Light," vol. 3, pp. 309–311, 2013.
2. M. N. Rathore and J. Sagar, "A Revie won Fake currency detection using feature extraction," vol. 10, no. 11, pp. 407–411, 2019.
3. K. Santhanam, S. Sekaran, S. Vaikundam, and A. M. Kumarasamy, "Counterfe it currency detection technique using image processing, polarizat ion principle and holographic technique," Proc. Int. Conf. Comput. Intell. Model. Simul., no. Figure 2, pp. 231–235, 2013, doi: 10.1109/CIMSim.2013.44.
4. P. Ponishjino, K. Antony, S. Kumar, and S. Jebakuma r, " Bogus currency authorization using HSV techniques," Proc. Int. Conf. Electron. Commun. Aerosp. Technol. ICECA 2017, vol. 2017- January, pp. 179–183, 2017, doi: 10.1109/ICECA.2017.8203667.
5. Q. Zhang and W. Q. Yan, "Currency Detection and Recognition Based on Deep Learning," Proc. AVSS 2018 - 2018 15th IEEE Int. Conf. Adv. Video Signal - Based Surveill., pp. 0–5, 2019, doi: 10.1109/AVSS.2018.8639124.
6. A. Upadhyaya, V. Shokeen, and G. Srivastava, "Analysis of counterfeit currency detection techniques for c lassification mode l," 2018 4th Int. Conf. Comput. Commun. Autom. ICCCA 2018, pp. 1–6, 2018, doi: 10.1109/CCAA.2018.8777704.
7. S. Arya and M. Sasiku mar, "Fa ke Currency Detection," 2019 Int. Conf. Recent Adv. Energy- Efficient Comput. Commun. ICRAECC 2019, pp. 2019–2022, 2019, doi: 10.1109/ICRAECC43874.2019.8994968.
8. A. Ku mar and A. Ku mar, "Dog Breed Classifier for Facial Recognition using convolutional Neural Networks," pp. 508–513, 2020.
9. M. Ha ider Ali, "Thesis Report on Fake Currency Detection using Image Processing Method," Akiful Mohaimin Rifat Islam Shahriar Chowdhury, no. 13301148, pp. 1–38, 1330.
10. M. N. Shende and P. P. Patil, "A Revie won Fake Currency Detection using Image Processing," Int. J. Futur. Revolut. Comput. Sci. Commun. Eng., vol. 4, no. 1, pp. 391–393, 2018.