Integrating Machine Learning with Ensemble mean confidence aggregation in Fake Currency Detection

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***Abstract*—Counterfeit currency, which refers to fake or imitation money designed to deceive, has seen a significant rise, particularly following recent demonetization efforts. This surge has led to an increase in counterfeit notes circulating within banking systems and a subsequent uptick in suspicious financial activities. Traditional methods for detecting counterfeit currency primarily rely on image processing techniques. This paper proposes a novel approach to counterfeit detection by utilizing a combination of two fine-tuned, pre-trained convolutional neural network models, NasNetMobile and InceptionV3, in conjunction with a custom proprietary model within an ensemble framework. The ensemble approach combines these models to significantly boost detection accuracy, achieving an impressive 94.72% accuracy rate. Furthermore, a unique mean confidence aggregation mechanism applied across these three models further enhances both the accuracy and reliability of the detection process. This research represents a major advancement in the fight against counterfeit currency, providing considerable benefits to banking institutions, financial organizations, and the retail sector by improving the effectiveness of fraud prevention strategies.**

***Index Terms*—Counterfeit Currency, Convolutional Neural Networks(CNN), NasNetMobile, InceptionV3, Ensemble Learning, Machine Learning, Currency Authentication**

I. Introduction

The growing incidence of counterfeit currency has become a critical issue worldwide, as evidenced by numerous media reports documenting significant seizures of fake notes and their detrimental effects on financial systems [1]. Counterfeit currency, characterized by the unauthorized duplication of monetary notes, has been a longstanding problem throughout history. Historical records show that as early as 600 BC in Lydia, counterfeit coins were created by shaving off precious metals from legitimate coins. Similarly, the introduction of paper money in China during the 12th century was met with strict countermeasures, including severe punishments to deter counterfeiting [2]. However, as forgery techniques continue to evolve, verifying the authenticity of documents has become increasingly challenging, particularly since the human eye is limited to detecting colors that are combinations of red, blue, and green (RGB) [16].

Counterfeit currency is a widespread issue affecting nearly every nation, with India facing particularly severe challenges. The proliferation of fake notes has created an urgent need to develop systems that can quickly and efficiently recognize paper currency. This proposed system outlines a method for verifying Indian banknotes [14]. For ordinary individuals, it can be challenging to determine whether a currency note is real or counterfeit, potentially leading to financial losses, especially during bank deposits or transactions. To address this, the system is designed to be user-friendly, enabling anyone to easily verify the authenticity of their currency by analyzing its visual features [17].

Automated machines capable of detecting banknotes are now commonly used in dispensers for modern products such as candy, soft drink bottles, and bus or railway tickets. The technology behind currency recognition primarily focuses on identifying and extracting both visible and invisible features of banknotes [15]. Despite these advancements, the continuous evolution of scanning and printing technologies has made it easier for counterfeiters to create increasingly convincing forgeries, challenging the effectiveness of traditional anti-counterfeiting measures.

Machine learning as a domain offers significant advantages in detecting counterfeit currency. By learning from vast amounts of labeled currency images, machine learning models can automatically identify patterns and features that distinguish authentic notes from counterfeits. Unlike traditional rule-based systems, which may struggle with the evolving techniques used by counterfeiters, machine learning models can adapt and improve over time as they are exposed to new data.

In response to these evolving threats, this paper presents a novel approach that leverages deep learning models to enhance counterfeit currency detection. Specifically, we utilize

NasNetMobile and InceptionV3, two fine-tuned pre-trained convolutional neural network (CNN) models, in conjunction with a custom proprietary CNN model. This combination forms an ensemble learning system that capitalizes on the strengths of each model to improve detection accuracy. Our approach aims to provide a more robust solution for detecting counterfeit currency and addressing the sophisticated techniques employed by modern counterfeiters.

II. Related Works

The detection of forged documents, including counterfeit currency, has been a significant area of research, with traditional methods largely centered on manual verification. These methods typically involve visually inspecting security features such as security threads, watermarks, optically variable inks, and intaglio printing. Additionally, non-visual techniques, like chemical analysis, are employed to evaluate the quality of the paper. Although these manual methods are generally dependable, they fall short in terms of scalability and efficiency, especially when dealing with large volumes of currency [7].

To overcome these limitations, various automated approaches have been developed. For instance, a method using the visible light spectrum combined with hyperspectral imaging (VIS-HSI) has been introduced, allowing for the detection of counterfeit notes by analyzing specific regions of interest (ROIs) on banknotes [3]. Another approach involves using Support Vector Machines (SVMs) to detect counterfeit notes by examining distinct security features, such as watermarks, latent images, and security threads [4].

Image processing techniques have also gained traction in counterfeit detection. One notable method utilizes OpenCV with Python, involving steps such as image acquisition, preprocessing, and feature extraction using the ORB (Oriented FAST and Rotated BRIEF) algorithm. Template matching is then performed with the Brute Force algorithm and KNN matcher, ultimately determining whether the currency is genuine or counterfeit based on the matching results [5]. Another system integrates a mobile camera for capturing images, coupled with a Flask web application that interfaces between the user and the image processing model. This method includes image registration to align and transform images for comparison, Brute-Force Matching with ORB Descriptors, and UV detection to verify UV marks on authentic notes. Additionally, the system offers currency conversion, translating detected Indian currency into equivalent values across more than 150 other currencies [6].

However, many of these existing approaches primarily focus on detecting counterfeits produced by conventional scanners and printers. It is crucial to recognize that high-quality counterfeit currency is rarely produced using such methods. Instead, sophisticated counterfeits are often created using the same raw materials and printing techniques as authentic currency. As a result, linking counterfeit notes to their originating printing presses is a vital yet underexplored area of research. To the best of our knowledge, this issue has not been specifically addressed in existing studies.

TABLE I
SUMMARY OF RELATED WORK

Name	**Year**	**Method**	**Remarks**
Automatic Counterfeit Currency Detection Using a Novel Snapshot Hyperspectral Imaging Algorithm[3]	2023	leverages a visible light spectrum (VIS-HSI) algorithm that allows for the detection of counterfeit notes	Pros:- Portablity and Accessiblity Cons:- Good lighting required
A Novel Approach for Detection of Counterfeit Indian Currency Notes Using Deep Convolutional Neural Network[8]	2020	The images are then processed through a CNN model, which includes steps like edge detection, image segmentation, and pattern matching	Pros:-High Accuracy of 96.6% Cons:-Dataset size is small,cant handle worst case data.
An Intelligent Method for Indian Counterfeit Paper Currency[9]	2020	image processing techniques to detect counterfeit notes.	Pros:-Good accuracy of 95.8% Cons:-Class imbalance cant be handled
Indian Counterfeit Banknote Detection using Support Vector Machine[4]	2020	The proposed system uses SVM to detect counterfeit banknotes	Pros:-Good accuracy of 94% Cons:- Complex and expensive.
Counterfeit Currency detection using image processing[10]	2013	Uses ultraviolet light to reveal fluorescent patterns unique to genuine notes	Pros:-Holographic Detection method Cons:-Continuous improvement required
Banknotes Counterfeit Detection Using Deep Transfer Learning Approach[11]	2020	Uses deep learning techniques, specifically convolutional neural networks (CNNs), to detect counterfeit currency	Pros:-Various Layers to check currency Cons:-Limited dataset size and single model used
Counterfeit Currency Detection based on AI[12]	2022	Uses deep learning techniques,Employs transfer learning with pre-trained models	Pros:-Cost effective as open source Cons:-Small Data size
Currency Recognition System[5]	2015	Uses image processing techniques and OpenCV with Python	Pros:-High accuracy to detect multiple currency Cons:-Heavily dependent on human input
Fake Currency Detection using Basic Python Programming and Web Framework[6]	2020	Web interface: Flask web application to interface between user and image processing model	Pros:-Made in Python which makes it simple Cons:-Dataset of only ideal conditions
Indian Currency Denomination Recognition and Fake Currency Identification[13]	2021	Convolutional Neural Network (CNN) model,Preprocesses images by resizing and normalizing pixel values	Pros:-Hardware free approach Cons:-Detects features only from front

III. Approach

The proposed system is designed to enhance the accuracy and reliability of binary classification for detecting whether a note is real or fake. To achieve this, we employ an ensemble prediction approach that leverages the strengths of three distinct models: NasNetMobile, InceptionV3, and a

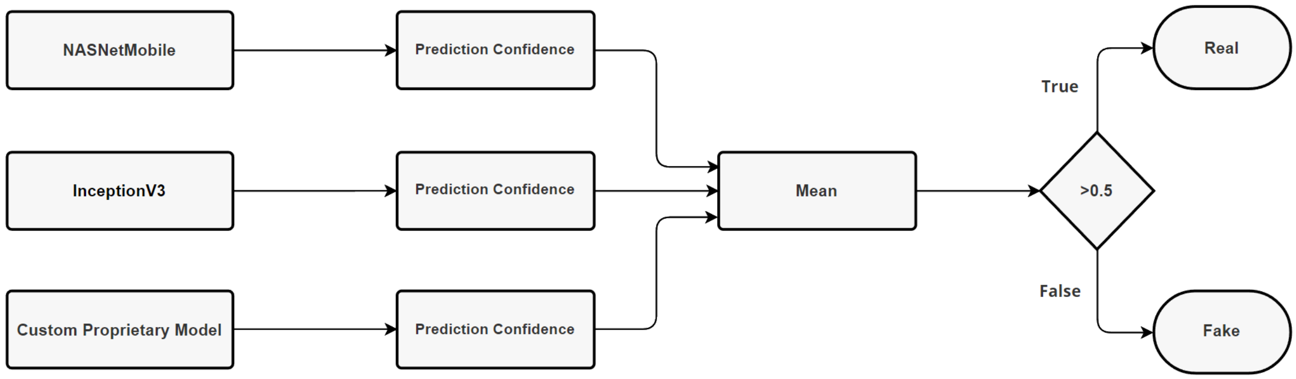

Fig. 1. Ensemble Mechanism

custom proprietary model. The ensemble method integrates the predictions of these models using a mean confidence aggregation mechanism, which ultimately determines the final classification.

A. Model Selection and Fine-tuning

NasNetMobile is a convolutional neural network (CNN) architecture known for its efficiency in mobile and embedded vision applications. Given its balance between accuracy and computational efficiency, it is well-suited for our task. The model is pre-trained on a large dataset, such as ImageNet, and then fine-tuned with our specific data. Fine-tuning allows the model to adapt its learned features to the nuances of our dataset, enhancing its ability to differentiate between real and fake notes.

InceptionV3 is another powerful CNN architecture, particularly known for its deep layers and capability to capture intricate patterns in images. Like NasNetMobile, InceptionV3 is pre-trained on a large dataset and subsequently fine-tuned with our data. This fine-tuning process ensures that the model is well-adjusted to the specific characteristics of the notes in our dataset, thus improving its classification performance.

B. Custom Proprietary Model

In addition to the two pre-trained models, we introduce a custom proprietary model specifically designed and optimized for our task. This model is built from the ground up and trained solely on our dataset, allowing it to learn features that are highly relevant to the classification of real versus fake notes. The proprietary model serves as a specialized component of the ensemble, providing unique insights that may not be captured by the pre-trained models.

C. Ensemble Prediction with mean confidence aggregation Mechanism

After the individual models—NasNetMobile, InceptionV3, and the custom proprietary model—have been fine-tuned and trained, their predictions are combined using an ensemble technique. The ensemble method employed in this system is a mean confidence aggregation mechanism, where each model's output is treated as a vote towards the final decision.

D. Mean confidence aggregation Mechanism

The mean confidence aggregation mechanism operates on the principle where the final prediction is derived by averaging the confidence levels of individual model outputs. Unlike traditional majority voting, which considers only the categorical outputs, this method accounts for the degree of certainty each model exhibits in its prediction. By integrating these confidence scores, the mechanism enables a more informed and precise decision, particularly valuable when models demonstrate varying degrees of certainty, thereby enhancing the overall reliability and robustness of the ensemble's final classification.

E. Data Flow and Implementation

- Data Preprocessing: The input data, consisting of images of notes, undergoes preprocessing steps to ensure compatibility with all three models. These steps include resizing, normalization, and augmentation to enhance the model's ability to generalize.
- Model Inference: Each preprocessed input is fed into the three models—NasNetMobile, InceptionV3, and the custom proprietary model. The models generate individual predictions based on their learned parameters.
- mean confidence aggregation and Final Decision: The individual predictions are collected and passed through the mean confidence aggregation mechanism. The outcome of the mean confidence aggregation process is the final prediction, indicating whether the note is real or fake.

IV. Architecture of Proprietary Model

The model begins with a convolutional layer that applies 32 filters of size 3x3 to the input image. This choice of 32 filters allows the model to detect basic features such as edges, textures, and simple shapes, which are crucial in the early stages of image processing. The 3x3 filter size is optimal for capturing fine-grained details while preserving spatial information. The Exponential Linear Unit (ELU) activation function is used in this layer, providing the benefit of reducing the risk of "dead neurons"—a common problem in deep networks

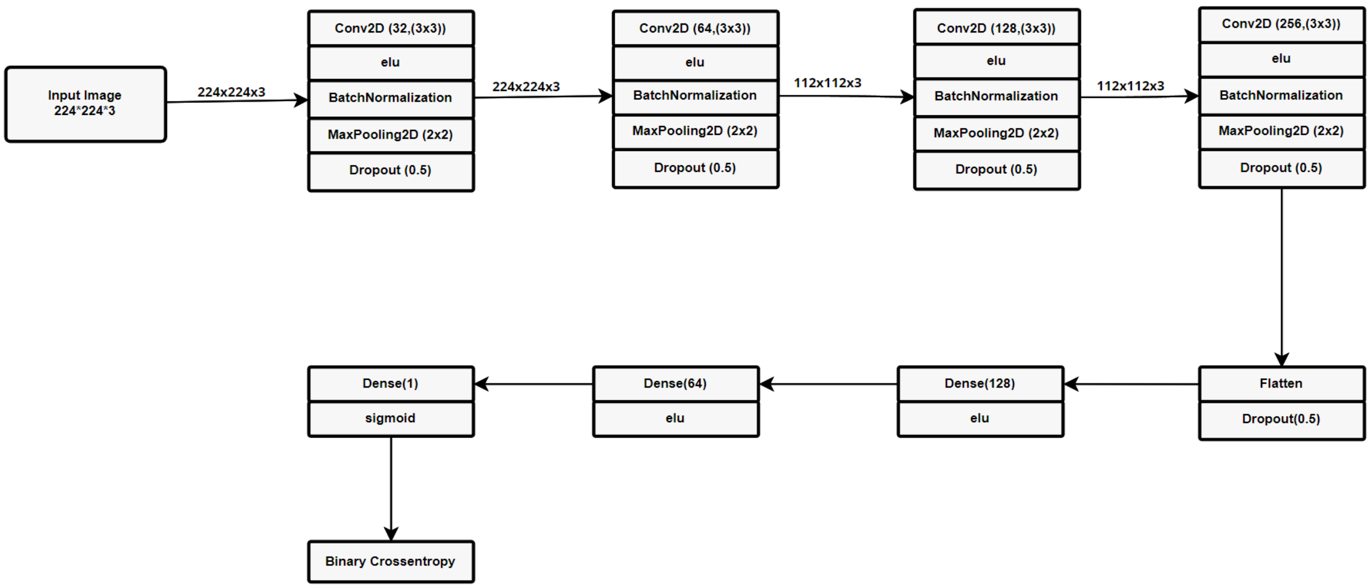

Fig. 2. Proprietary Model

where some neurons become inactive and stop learning. ELU also speeds up the learning process by maintaining a smoother gradient and allowing the model to converge faster. The output of this layer is then passed through a batch normalization layer, which normalizes the activations, making the training process more stable and allowing for higher learning rates. Batch normalization also helps to reduce the dependence on careful weight initialization and acts as a regularizer, potentially reducing the need for other forms of regularization like dropout. Following this, a max-pooling layer reduces the spatial dimensions of the feature maps, effectively downsampling the data. This reduction in spatial size not only decreases the computational complexity, making the model more efficient, but it also helps in controlling overfitting by retaining only the most prominent features. Additionally, max-pooling introduces a degree of translation invariance, meaning the model becomes more robust to changes in the position of features within the image. A dropout layer with a 50% dropout rate is added to further prevent overfitting by randomly dropping units during training. This technique forces the network to learn more robust and general features, as it cannot rely too heavily on any single neuron. This pattern is repeated with increasingly larger filter sizes in subsequent convolutional blocks. The second convolutional block applies 64 filters, the third block applies 128 filters, and the fourth block applies 256 filters. Increasing the number of filters at each stage allows the model to capture more complex and abstract features, which are essential for differentiating between classes in more intricate image data. Each of these blocks follows the same structure of convolution, batch normalization, max-pooling, and dropout. The consistent use of batch normalization ensures that the model remains stable and learns effectively throughout the deeper layers, while max-pooling continues to reduce the dimensionality, focusing the model on the most significant features. The repeated use of dropout layers helps maintain the generalization ability of the network, reducing the risk of overfitting as the model becomes deeper and more complex. After the convolutional layers, the model flattens the output into a one-dimensional vector, which is then passed through fully connected (dense) layers. Flattening is a necessary step to transition from the 3D tensor output of the convolutional layers to the 1D input required by the dense layers. These dense layers further process the learned features, combining them in ways that help the model make a final classification decision. The first dense layer has 128 units, which provides enough capacity to handle the complexity of the features extracted by the convolutional layers, enabling the model to capture the nuanced patterns necessary for accurate classification. The second dense layer, with 64 units, continues this process, refining the decision-making process while reducing the dimensionality of the feature space. Both layers use the ELU activation function, ensuring that the benefits of faster convergence and effective handling of non-linear relationships are maintained throughout the network. Finally, the output layer consists of a single unit with a sigmoid activation function, which is ideal for binary classification tasks. The sigmoid function outputs a probability value between 0 and 1, which can be interpreted as the likelihood that the input belongs to one class or the other. This design choice allows the model to produce a clear decision boundary, making it straightforward to classify the input image based on the output probability. The use of a single unit in the output layer ensures that the model is focused on the binary nature of the task, optimizing its performance for distinguishing between the two possible classes ‘real’ and ‘fake’.

V. Results

A. Dataset Collection

The dataset for this study was meticulously curated to support robust evaluation of counterfeit currency detection algorithms. The real currency dataset comprises high-resolution images of genuine banknotes, obtained from various authentic sources to ensure diversity and representativeness. These images capture the intricate details and security features of legitimate currency, providing a comprehensive foundation for model training and validation.

In parallel, the counterfeit currency dataset was assembled using replicas of banknotes, meticulously crafted to mimic the physical characteristics of real currency. These replica notes were designed to challenge the detection system with varying degrees of fidelity to the authentic features, thus facilitating a thorough assessment of the system's robustness against different counterfeiting techniques.

This dual-dataset approach enables a rigorous evaluation of the proposed detection models, ensuring that they are capable of distinguishing between genuine and counterfeit notes with high accuracy. By leveraging both real and replica currency images, the study aims to enhance the reliability and generalizability of the detection system across diverse scenarios

	Real	Fake	Total
Testing	5000	5000	10000
Evaluating	5000	5000	10000

Fig. 3. Dataset Description

B. Training of Proprietary Model

Model	Accuracy	Loss	Validation Accuracy	Validation Loss
NASNetMobile	91.2%	0.2032	97.1%	0.1402
InceptionV3	91.5%	0.1839	89.2%	0.2588
Proprietary Model	92.6%	0.2133	91.4%	0.1845

Fig. 4. Accuracy Table

Starting from the first epoch, both the training and validation losses decrease steadily, which is a positive indicator that the model is learning effectively. The training loss shows a more significant and consistent decline, indicating that the model is becoming increasingly proficient at fitting the training data.

The validation loss, on the other hand, decreases steadily at first, which is a good sign that the model is generalizing well to unseen data. There is a bit of fluctuation around the 30th epoch, but this is not unusual and indicates that the model is fine-tuning its generalization capability. Importantly, the validation loss remains close to the training loss, which is an excellent outcome. This suggests that the model has a good balance between bias and variance, and there is no significant overfitting, as both losses converge and remain low.

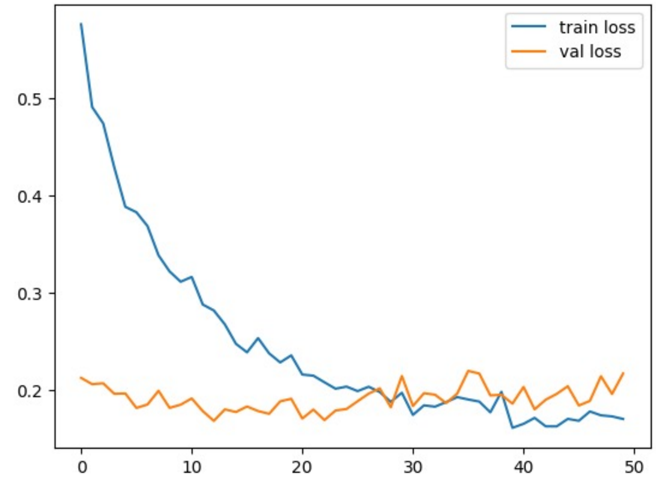

Fig. 5. Training Loss

At the beginning of training, the accuracy starts relatively low but shows a rapid increase, indicating that the model quickly learns and adapts to the training data. As the epochs progress, the training accuracy continues to rise, albeit with some fluctuations, and finishes at 92.6%. This trend suggests that the model is learning well and improving its ability to correctly classify the training data. The validation accuracy starts off high and remains consistently above 90% throughout the training process, which is a very positive sign. The fact that the validation accuracy remains stable and closely follows the training accuracy indicates that the model generalizes well to new, unseen data. The fluctuations in both the training and validation accuracy are typical and reflect the fine-tuning process as the model adjusts to better capture the underlying patterns in the data.

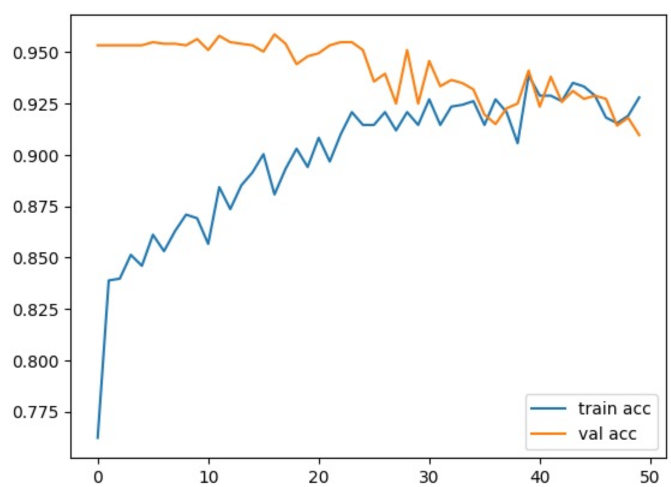

Fig. 6. Training Accuracy

C. Evaluation

The table below presents the performance metrics of the proposed ensemble model, which combines NASNetMobile, InceptionV3, and a custom proprietary CNN model for the task of counterfeit currency detection. The metrics reported include Accuracy, Precision, Recall, and F1-Score, which are standard measures used to evaluate the effectiveness of classification models.

Accuracy is a measure of the overall correctness of the model's predictions, calculated as the ratio of correctly predicted instances to the total number of instances. The ensemble model achieves an accuracy of 94.72%, indicating that it correctly classifies approximately 94.72% of the notes as either real or fake.

Precision represents the ratio of true positive predictions to the total number of positive predictions made by the model. With a precision of 0.9354, the model demonstrates a high level of confidence in its positive predictions, meaning that 93.54% of the notes it identifies as real are indeed real.

Precision (also known as Sensitivity or True Positive Rate) measures the ratio of true positive predictions to the total number of actual positive instances in the dataset. The model achieves a recall of 0.9608, which reflects its ability to correctly identify 96.08% of the real notes present in the dataset.

F1-Score is the harmonic mean of Precision and Recall, providing a balanced measure of the model's performance when considering both false positives and false negatives. The F1-Score of 0.9479 indicates that the ensemble model maintains a strong balance between precision and recall, making it highly effective in distinguishing real notes from fake ones.

These metrics collectively demonstrate the robustness of the proposed ensemble model in accurately and reliably detecting counterfeit currency. The high values across all performance indicators underscore the effectiveness of integrating multiple CNN architectures to enhance classification performance, thereby making the system a viable solution for real-world counterfeit detection applications.

	Accuracy	Precision	Recall	F1-Score
Weighted Average	94.72%	0. 9354	0.9608	0.9479

Fig. 7. Ensemble Report

The Confusion matrix provides a comprehensive view of the model's classification performance. The high number of true positives (4804) and true negatives (4668) underscores the effectiveness of the ensemble approach in accurately distinguishing between real and fake currency. However, the presence of false positives (332) and false negatives (196) indicates areas where the model could be further refined to minimize misclassifications.

By analyzing this confusion matrix, we can conclude that the ensemble model demonstrates strong predictive capabilities, with a particularly high accuracy in detecting counterfeit notes. The relatively lower rates of false positives and false negatives further validate the model's robustness and generalizability in real-world applications of counterfeit detection. This analysis is essential in highlighting the strengths and potential areas for improvement in the model, providing valuable insights for future enhancements.

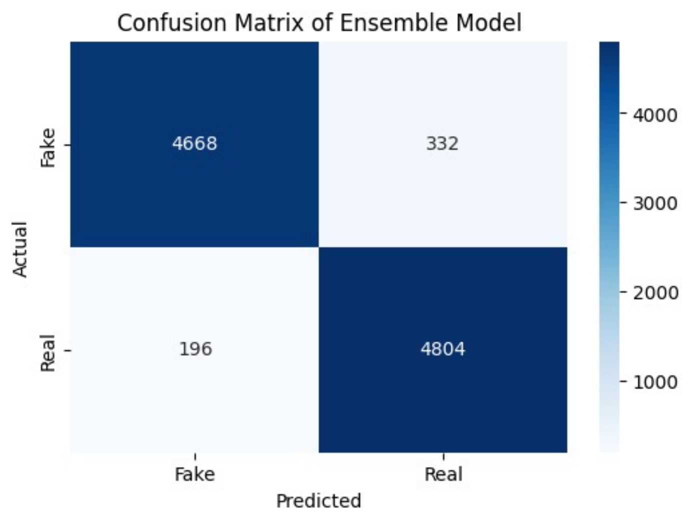

Fig. 8. Confusion Matrix

VI. Conclusion

In this research, we have developed and rigorously tested a reliable system for detecting counterfeit currency, utilizing a combination of advanced deep learning models—NasNetMobile, InceptionV3, and a custom proprietary CNN. By carefully preprocessing the data and fine-tuning each model, our ensemble approach has demonstrated strong accuracy and dependability in distinguishing between real and fake notes. The ensemble's mean confidence aggregation mechanism ensures that the final decisions are both accurate and consistent, reducing the potential for overfitting that might arise with individual models.

The high classification accuracy, supported by the performance metrics and confusion matrix analysis, showcases the effectiveness of our approach in practical applications. This system highlights the power of deep learning in solving real-world challenges in currency authentication and establishes a new standard for detecting counterfeit notes using AI-driven techniques.

The successful results of this research emphasize the value of combining multiple models within an ensemble framework, opening the door for further innovations in this area. Our work makes a meaningful contribution to financial security, offering a dependable solution that can be applied in real-world scenarios to address the ongoing issue of counterfeit currency.

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