A Two-Phase Deep Learning Model for Counterfeit Detection of Indian Banknotes using YOLO-NAS and UV Imaging for Visually Impaired People

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A Two-Stage Deep Learning-Based Framework for Counterfeit Detection of Indian Currency Using YOLO-NAS and UV Imaging for Visually Impaired People

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Abstract: Counterfeit currency creates a significant financial and security threat, often mimicking genuine notes so precisely that the human eye struggles to discern the differences. This issue becomes even more severe for the visually impaired, who struggle to distinguish between authentic and counterfeit banknotes. To overcome this problem, a new two-phase approach is proposed that uses the You Only Look Once-Neural Architecture System (YOLO-NAS) to detect and verify Indian rupee notes under ultraviolet (UV) light. This model comprises two phases: In the first phase, the observable and invisible characteristics of a currency note are identified. In contrast the second phase authenticates it based on advanced security features that are exclusively detectable under ultraviolet (UV) light. The model's performance is evaluated on two distinct datasets: the Indian and Thai banknotes dataset and the self-designed dataset. The first experiment was conducted on the Indian and Thai banknote datasets, achieving an accuracy of 91.02%. Then, another experiment was performed on a self-created dataset, yielding an accuracy of 93.99%. Furthermore, an audio-based output system is integrated to assist visually impaired individuals in identifying and verifying banknotes. Experimental results indicate that the proposed method enhances counterfeit detection, making it suitable for practical use.

Keywords: Counterfeit Currency Detection; Deep Learning; Ultraviolet Imaging; Visually Impaired Assistance; YOLO-NAS

1. Introduction

The World Health Organization estimates 2.2 billion blind or visually impaired persons, and approximately 20% of the world's population resides in India[36]. Our research aims to help visually impaired individuals accurately and efficiently recognize real and fake Indian currencies. Identifying the denomination of currency notes is relatively straightforward for individuals with normal vision. However, distinguishing counterfeit notes remains a significant challenge for them due to the advanced technology used in printing fake currency. For visually impaired individuals[23], this challenge is even more difficult. Therefore, there is a need to develop a reliable and effective currency identification model to assist blind individuals in accurately distnguishing between authentic and counterfeit Indian paper currency. The human eye struggles to discern the differences in counterfeit notes. Banks, large-scale industries, and financial institutions rely on sophisticated machines equipped with advanced sensors, UV lights, and fluorescent detectors to combat this. These machines are designed to analyze hidden features such as optic fibers, micro lettering, security threads, and UV-sensitive elements, which are nearly impossible to differentiate with the naked eye[37]. For the visually impaired, the challenge of verifying and authenticity of currency notes becomes more profound, even with raised printing and identification marks on them, because they can't visually examine these features. Moreover, the average person, whether sighted or blind, cannot feasibly rely on such specialized machines for everyday transactions. To address this pressing issue, a robust model has been developed that extracts low-level features to assist in note detection while leveraging high-level features for counterfeit identification.

1.1. Problem statement

Most existing research on currency counterfeiting detection relies on edge detection techniques or verifying whether all visible features of a note match those of a genuine one[38]. This approach focuses on features

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discernible under normal lighting conditions, such as watermarks, color patterns, and microtext. While these methods can effectively detect counterfeit notes, they have significant limitations. Using standard imaging techniques, counterfeiters replicate visible features, making it challenging to identify original and counterfeit notes. However, currency notes also incorporate security features that are not visible under normal lighting conditions but become apparent under ultraviolet (UV) light. These hidden features, such as UV-fluorescent security threads, fiber optics, and unique ink patterns, provide an additional layer of authentication that is difficult to replicate accurately[37,50)]. The concept of using imaging techniques to reveal latent or multi-layered security elements has been successfully demonstrated in other domains[54,55)]. Despite their critical role in counterfeit detection, these UV-reactive security features have been largely overlooked in existing research. This creates a significant research gap; counterfeit detection models predominantly rely on visible feature analysis, making them vulnerable to high-quality forgeries that mimic surface-level characteristics. By using visible features to identify the denomination and hidden UV-reactive features to detect counterfeits, this dual-phase approach enhances the robustness and accuracy of verifying currency authentication.

Secondly, due to the use of multiple internal architecture layers, some research requires longer processing times and finds problems with folding, lighting, complexity of the system, and high costs. They focused on various neural network architectures and approaches but often did not highlight the specifications required for effective implementation[39)]. Therefore, it is essential to focus not only on algorithms and architectures, but also on lightweight architectures[40)]. Various types of neural networks and self-designed CNN models, such as SSD[41)] and Tiny-YOLO[42)] have a reduced number of parameters, which allows them to operate efficiently on limited hardware resources and perform computations quickly. However, it cannot learn and represent complex characteristics, decreasing accuracy. Models with several layers, such as ResNet and VGG-16[43,44)], have a higher parameter count and demand more computational resources. Still, due to their numerous layers, they are challenging to implement on low-power wearable devices, and they also require high-performance graphics. YOLO-NAS, with 22.2 million parameters, is introduced to balance complexity and computations well, significantly enhancing 8-bit quantization to provide fewer hardware requirements for edge computing devices while maintaining greater precision.

This research developed Indian currency banknote detection using (YOLO-NAS) because its neural architecture design automatically discovers the optimal architecture by pruning unnecessary layers and neurons, leading to a lightweight model[45,46)]. The system would enable the visually impaired to detect and identify genuine and counterfeit currency under ultraviolet rays, which is then sent for preprocessing. After getting it, the model would process the data, which appears to be a picture, and provide an appropriate output in a text form. It would then transform the text output into an audio format based on the output the user had provided. This model solves some currency-related issues and shows their importance to society.

1.2. Objective

Develop an audio-based Indian currency detection and counterfeit model to assist blind individuals in handling currency independently, especially when exchanging money during daily activities.

- Detection of authentic and counterfeit Indian banknotes under ultraviolet rays in a light environment.
- A two-phase approach was proposed, where features are detected using YOLO-NAS in the first phase, and the detected features will be used for verification in second phase. Images are captured under UV lights to highlight hidden features, which helps enhance the counterfeiting results.
- Adam's optimization technique, with batch sizes of 32, is applied to evaluate how well each CNN architecture's hyperparameters function in training our model to minimize the loss function.
- Based on accuracy, recall, and precision, evaluate the performance. The best-performing model has been developed to counterfeit Indian banknotes based on all of these findings.

This research highlights initiatives focused on enhancing the financial and social independence of individuals with visual impairments. The remaining sections will be distributed in the following manner: Section 2 reviews the literature relevant to the proposed plan. Section 3 discusses the dataset preparation, proposed model, and workflow description. Section 4 presents the results analysis and comparison of outcomes.

2. Related Work

Advances in color printing technology have led to a greater rate of fake note production and counterfeit issues in financial institutions. Traditional methods are confined to banks and large institutions but leave small businesses vulnerable and visually impaired. To address this issue, researchers have created several methods over time. Several approaches have demonstrated promising results in successfully recognizing banknotes using deep learning and object detection algorithms, and summary of related work is also presented in Table 1

Wafia Rarani et al.[27)] presented an approach to detect

Indian currency counterfeit notes by combining CNN with YOLOv3, which increases identification speed and accuracy while improving security. A dataset of 78 images of new Indian currency notes (₹2000, ₹500, ₹100, ₹200, ₹50, and ₹10) was used for training over 6000 epochs with a 0.001 learning rate, achieving 99.57% accuracy and 0.28% training loss.

Naalla Aashrith Raksh et al.[28] proposed an innovative software-based system for detecting fake currency to counter the growing threat of counterfeit Indian currency. The system analyzes bleed lines, security threads, latent pictures, and watermarks to assess the security characteristics of the ₹500 and ₹2000 notes. It employs three key algorithms: ORB detection with SSIM for feature comparison, bleed line authentication, and number panel verification. The method is faster and more accurate than manual identification, detecting 79% of genuine notes and 83% of counterfeits.

Nama'a M. Z. Hamed et al.[29] address the challenge of detecting counterfeit Iraqi banknote. The study uses RNG, XGBoost, Decision Tree Classifier, SVM, CatBoost, and deep learning models (VGG16, InceptionV3, MobileNetV2) to detect counterfeits accurately. The dataset of 1,359 photos of genuine and counterfeit Iraqi notes was expanded to 8,154 samples for model training. A real-time detection system was created using the Raspberry Pi 5, a camera, a servo motor, a UV light, and an LCD screen. Experimental findings showed 98% accuracy with CatBoost and SVM models and 99% with CNN models.

Pham T.D. et al.[30] used smartphone cameras to present a deep learning technique with self-assembled global authentic and counterfeit datasets of JOD, KRW, EUR, USD, and banknotes for the detection of counterfeit currency. The CNN and YOLOv3 approaches are combined with different feature-level fusion techniques and scores.

Wang, L. et al.[31]presented an automated approach using a dataset of 290 banknote pictures. It classifies the internal features of currency using optical coherence tomography. The study employed Logistic regression, KNN, random forest, and support vector machine techniques. At 96.55% sensitivity and 98.85% specificity, the SVM classifier performed the best.

Pachon et al.[32] describe a way to apply the prune methodology within the convolution layers for the Colombian original and fake banknotes detection with 20,800 by using sequential CNN architectures: custom, AlexNet, VGG11, and VGG16. This pruning model demonstrated a parameter reduction of approximately 75%, resulting in an accuracy decline of up to 0.5% in all models. There were only slight accuracy decreases of 0.3% and 0.9% for the custom and VGG11 models, respectively. Additionally, HiResCAM analysis demonstrated that these models lost less accuracy than alternative approaches.

Anggarjuna Puncak Pujiputra[33] proposes a method for identifying Indonesian Rupiah banknotes using ultraviolet light. The technology utilizes UV imaging to reveal distinctive hidden patterns and glowing attributes on authentic notes, differentiating them from counterfeit currency. The technology effectively extracts detailed textural information from photos of banknotes using Gabor wavelet filters with three scales and eight orientations. The Linear Discriminant Analysis (LDA) classifier then sorts the images into groups. The results demonstrate the system's efficacy, achieving a 98.5% recognition accuracy on a dataset of 160 UV pictures of Rupiah banknotes.

Leo Razzel Viloria et al.[52] used a neural network implemented with TensorFlow and installed on a Raspberry Pi to create a stand-alone currency detection system for Philippine peso notes. The device integrates a Raspberry Pi camera and ultraviolet light to identify security features while providing several accessible outputs including braille labels, haptic feedback, and voice announcements. To ensure accurate detection in various situations, the effects of ambient light were eliminated using an enclosure. The model was trained on 80 photos for each denomination, attaining an accuracy of 87% and a usability value of 4.73 out of 5. The study found that while UV security features were efficient, they were not throughly examined, which may have improved the ability to detect counterfeit goods.

3. Materials and Methodology

This section describes the dataset and the proposed system. A dataset of 500 Rs. notes under UV light, consisting of 1319 photos across 11 categories, has been created[35]. Based on the HYOLO-NAS architecture, a model extracts low-level and high-level information to recognising and identifying real and counterfeit money. The process comprises four distinct steps. The components include:

- Dataset creation and preprocessing
- Feature extraction via YOLO-NAS
- Development and training of the model
- Testing

3.1. Dataset Preparation

In this research, a robust dataset was prepared to train a model for counterfeit detection under UV light conditions, as there is no publicly available dataset containing ultraviolet images[35]. A custom dataset was created for detecting counterfeit 500-rupee Indian currency notes using Roboflow, a platform for dataset creation. Below is a detailed explanation of the steps involved:

3.1.1. Image Collection

An iPhone 11 was used to capture high-quality images of 500-rupee currency notes under UV light. UV illumination was chosen so that hidden security features, such as the security thread, fluorescent fibers, and the Indian flag glow

Table 1: Summary of related work on currency detection close to our work

No	Year	Author	Problem statement	Dataset	Methodology	Accuracy
	2020	R. Joshi et al.[1]	System for Detecting and Recognizing Currency for People with Visual Impairments	Self-designed Indian currency	YOLOv3 banknote detection collects currency images in different conditions. Image augmentation to increase robustnes. Manually annotates the augmented images to create training and validation datasets.	95.71%
2.	2021	Pratiksha Ganjave et al.[2]	A Visually Impaired Currency Detector	Indian Banknotes	Currency recognition system using SIFT, FAST, ORB and SURF algorithm	95%
	2021	Devid Kumar et al.[3]	Using computer vision, identify counterfeit Indian currency	200 and 500 Indian paper Currency	Feature extraction using ORB and Brute-Force matcher.	95%
	2021	Muhammad Imad et al.[4]	Pakistani Currency Recognition Using Convolutional Neural Network for Aiding Blind Individuals.	Pakistani banknotes and Coins.	Convolutional Neural Network (CNN), Alex-Net Architecture and SupportVector Machine (SVM)	Accuracy on paper note is 96.85% Accuracy on coins is 76.19%
	2021	C Rahmad et al.[5]	Verification of currency authenticity via the KNN and CNN.	Indonesia paper currency	K=5 is used in the K-Nearest Neighbour approach for process detection. In CNN, The background image is manually cropped to detect new surface textures.	Accuracy on KNN is 87.75% CNN is 96.67%.
6	2022	Dereje Tekilu Aseffa[6]	Ethiopian Banknote Recognition Using CNN	8333 images Ethiopian Banknote	4 CNN (ResNet50, InceptionV3, XceptionNet, and MobileNetV2) have been executed using six optimizers (Adagrad, Adam, SGD, Nadam, Adadelta, and RMSProp—over 100 epochs.	MobileNetV2 + RMSProp optimizer+ 32 batch size achieves superior accuracy (96.4%).
7	2022	Lei Wang et al.[16]	Counterfeit banknotes detection using quantita tive features captured by spectral-domain optical coherence tomography	290 of YAN bank notes	SVM	Precision: 96.55% Recall: 98.85%
8	2022	Awad et al.[17]	Iraqi banknotes classifica tion using deeep learning for blind people	3,961 of Iraqi ban knote	Multi-layer CNN model	98.6 %

9	2023	Sarangam Kodati et al.[7]	Detecting Fake Currency with Machine Learning	Indian Paper Currency	Preprocessing is performed to reduce undesired distortions in the data or improve image attributes essential for further processing.	CNN -67.88% SVM- 75.91% KNN -72.26%
10	2023	Chanhum Park et al.[8]	Multinational banknote detection model	Korean won banknote and coin, US dollar, Euro and Jordanian dinar database	69 layers and four prediction feature maps enhance the YOLOv3-based mosaic data-augmented international banknote detection model, ensuring high precision.	0.8396 accuracy, 0.9334 recall, and 0.8840 F1 score.
11	2024	Ashraf Hussan Babor et al.[9]	CNN based coin detection system	Bangladeshi Coin Detection	Implemented different models, VGG16, VGG19, and EfficientNetB0 where VGG19 outperformed both models.	VGG16 training accuracy: 99.99%, validation accuracy: 90.90% EfficientNetB0 achieve 99.99% training accuracy and 96.51% validation accuracy. VGG19 training accuracy is 99.38% and a validation accuracy is 99.96%.
12	2024	Yogesh Suryawanshi et al.[10]	Machine learning approach to identify Indian coins for blind people.	6,672 images of Indian coins.	The Dataset includes images from multiple locations, backdrops, viewpoints, and directions. Pretrained EfficientNet, VGG16, and ResNet50 models are used to categorize Indian coins.	EfficientNet-Recall(.95) and F1(.97) VGG16-Recall(.99) and F1(.95) ResNet50-Recall(.95) and F1(.95)

under UV light.

3.1.2. Dataset Size

A total of 547 images of 500-rupee notes were captured. The dataset included both genuine notes, as shown in Figure 1, and fake notes, as shown in Figure 2, to ensure a diverse and balanced representation. Images were taken from different angles to mimic real-world scenarios where notes may not always be perfectly aligned. Front view, back view, single folded, and partially visible images were included.

3.1.3. Data Augmentation

After applying brightness adjustments between -15% and +15%, blur up to 2.5 px, and noise addition up to 0.1% of pixels augmentation techniques, the dataset was extended to 1319 images.

3.1.4. Dataset Splitting

The augmented dataset was divided into three subsets. 88% training set contains 1158 images, 8% validation set contains 108 images, and 4% test set contains 53 images.

3.1.5. Annotations

Each image was manually annotated with 11 classes using bounding boxes to identify and label key regions of interest, such as the security thread, Indian flag, RBI seal, Ashoka Pillar, fiber optics, and many more. The annotations were exported in a format compatible with the YOLO object detection framework, which was later used for model development.

3.1.6. UV Imaging Setup

To capture hidden security features on Indian currency notes, a UV-A light source was used, which is the safest and most commonly used range for non-invasive imaging. The UV light had a wavelength of approximately 365 nanometers (nm) and an output intensity of around 10–15 mW/cm², sufficient to reveal fluorescent and phosphorescent features without damaging the notes. Images were captured in a controlled dark environment at a distance of approximately 20 cm from the currency to ensure uniform illumination. This setup was chosen based on safety, effectiveness in feature enhancement, and

(a)

(b)

(c)

(d)

Fig. 1: Images of real banknotes, 1a) front ,1b) back, 1c) folded, and 1d) partially visible under UV lighting

consistency with practices used in document forensics.

(a)

(b)

(c)

(d)

Fig. 2: Images of fake banknotes, 2(a) front, 2(b) back, 2(c) folded, and 2(d) partially visible under UV lighting

3.2. Features Used for Detection and Counterfeiting

This model utilises nine features, as outlined in Table 2, to construct a comprehensive counterfeit framework. The six detection features focus on structural and visible elements, which help in detection, and three counterfeiting features emphasize security mechanisms embedded in the currency and are only visible under UV light. This dual approach ensures enhanced robustness in distinguishing genuine notes from counterfeits.

Table 2: List of features used in our proposed work for counterfeiting and detection

Low level Security Features	High level Security Features
Bleed lines	Security Thread
Number Panel	Fiber Optics
RBI Seal	Indian Flag
Ashoka Pillar	
Denominations	
RBI	

3.2.1. Low- Level features for detection

Bleed Lines: There are 5 short vertical lines labelled as 1 in Figure 3 on both corners of the notes, which are printed using a raised printing technique to aid visually impaired people.

Number Panel: There are two alphanumeric sequences labelled as 2 in Figure 3 written in increasing size; one is in the top left corner, and the second is in the bottom right corner. This sequence is unique on each note, and the top left corner is printed larger than the bottom right corner, adhering to specific font and spacing standards that make it difficult to replicate accurately.

RBI Seal: This circular official authentic mark, featuring the RBI emblem, is printed near the center of the note labelled as 3 in Figure 3, ensuring the note's legitimacy.

Ashoka Pillar: The iconic emblem of the Ashoka Pillar, labelled as 4, is rendered with high precision in the original currency found on Indian notes.

Denominations: Denominations "500" are printed in five unique fonts, sizes, and placements, labelled as 5, making them a key feature for detection.

RBI: The letters "RBI" on the note are printed with specific inks and alignments that provide additional layers of validation.

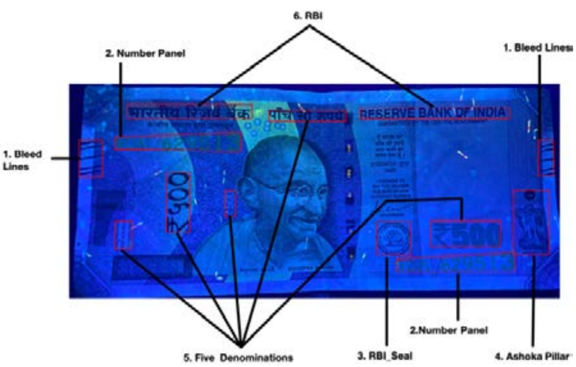


Fig. 3: Front view of real 500 Rs. under UV light that show six low level security features for currency detection

3.2.2. High-Level features for currency counterfeiting

To assess the authenticity of a note and detect counterfeiting, examine three hidden features that can only be seen under UV light[48, 51]:

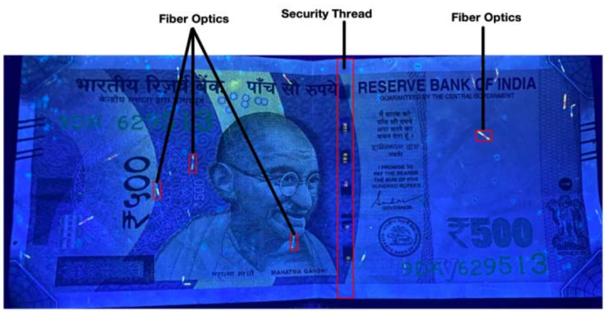
Security Thread: This fluoresces under UV light, appearing as continuous, bright, glowing bands. This thread contains micro-lettering with the text Bharat (in Hindi) and RBI, which is more visible under UV light. This level of clarity in text is the key indicator of authenticity, as shown in Figure 4(a). Counterfeiting notes often lack this clarity and exhibit uneven brightness. Fake security often fails to glow under UV light or glow uniformly, indicating forgery, as shown in Figure 5(a).

Fiber Optics: These are tiny distinct colored fibers (red, green, blue) that are embedded in the paper itself at the time of manufacturing. These are not glued or printed, making it nearly impossible to replicate their exact pattern or placement on counterfeit notes. These are randomly scattered on the note and are designed to fluoresce under UV light, as shown in Figure 4(a), while in fake notes, these fibers are absent or do not glow, which reveals the forgery under scrutiny, as shown in Figure 5(a).

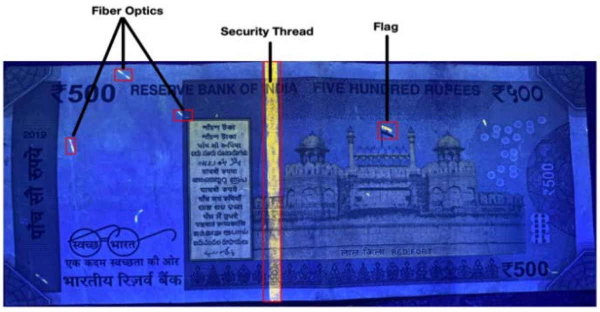
Indian Flag: The representation of the Indian flag on the reverse side of the currency notes makes it a robust anti-counterfeiting feature because when the note is exposed to UV light, its colors (saffron, white and green) and the Ashoka Chakra fluoresce distinctly compared to surrounding areas, as shown in Figure 4(b). This makes it easy to verify the note's authenticity. A simple UV light test can easily identify the presence (or absence) of the fluorescent glow on the Indian flag, which is a clear indicator of authenticity. If the flag does not glow under UV light, or the glow is weak or inconsistent, the note is likely to be counterfeit, as shown in Figure 5(b).

3.3. Hypertuned YOLO-NAS Model

YOLO-NAS is an advanced object detection algorithm known for its high precision, speed, and efficiency45,19). These attributes make it particularly well-suited for applications requiring accurate feature identification for currency classification and counterfeit detection. The YOLO-NAS algorithm is adopted as a baseline model for banknote detection and counterfeiting in this research. This creates an optimize solution for currency identification tasks through neural architecture search, which autonomously chooses an effective architecture. This research modified YOLO-NAS by hypertuning it with the concept of checkpoints, called HYOLO-NAS. The

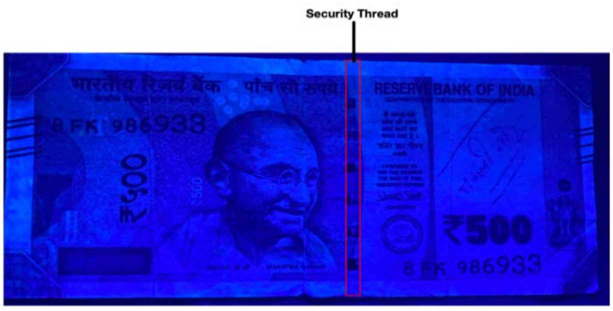


(a)

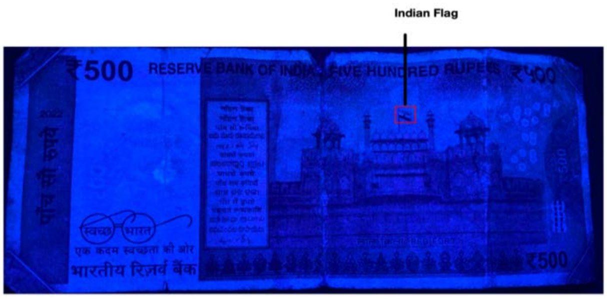


(b)

Fig. 4: (a) Front view of real 500rs under UV light that show two high level features for currency counterfeiting, (b) Back view of real 500rs under UV light that show three high level security features for currency counterfeiting



(a)



(b)

Fig. 5: (a) Front view of fake 500rs with counterfeit security and thread and absence of fiber under UV light**,** **(b)** Back view of fake 500rs with zero fiber detection and non-emitting Indian Flag under UV light

workflow begins with images containing objects to be detected, which serve as the input for YOLO-NAS, and the objective is to identify these objects within bounding boxes. A principal attribute of YOLO-NAS is Autonac, its neural architecture search element, which automates the identification of the optimal model architecture for currency detection by examining various hyperparameters and enhancing the architecture for accuracy, speed, and efficiency, as illustrated in Figure 6. This search procedure explores a wide range of possible structures using reinforcement learning. Once the optimal architecture is determined, training commences, integrating the checkpoint concept. The model's state, including weights and configurations, is periodically saved during training after the model architecture has been identified. Checkpoints provide the continuation of training from a designated point, enable fine-tuning, and allow for selecting the optimal model based on validation criteria. Ultimately, HYOLO-NAS facilitates the identification of an optimal model by the implementation of quantization and hardware-specific optimizations aimed at minimizing the size and enhancing its performance. By following this structured workflow, HYOLO-NAS becomes an efficient and adaptable architecture for implementing currency detection systems[49].

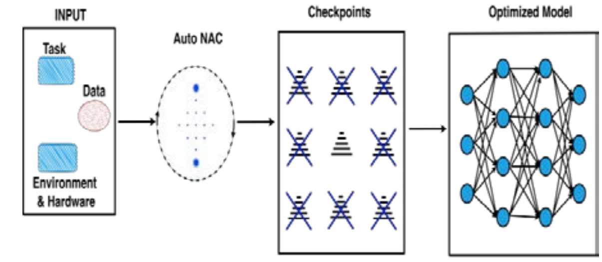


Fig. 6: Architecture of HYOLO-NAS

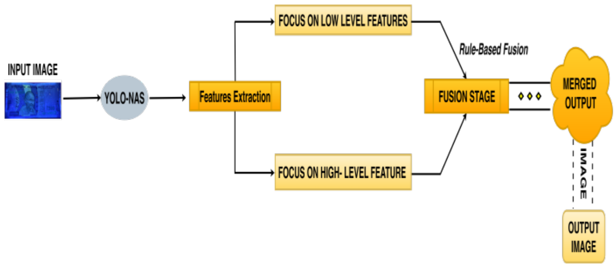


Fig. 7: Working model of proposed method

3.4. Methodology

In this study, an optimized model, HYOLO-NAS, was achieved by hypertuning to detect low-level features like denominations and critical high-level features such as security threads and fiber optics simultaneously49). Figure 7 illustrates a comprehensive representation of the proposed system. Annotated images of ₹500 currency notes are provided to the model, where a total of nine features were annotated, including the RBI text (in both Hindi and English), RBI seal, Ashoka pillar, bleed lines, serial number, and five distinct variations of the ₹500 text. Additionally, the security thread, fiber optics, and Indian flag were also annotated. The first six features were selected as low-level features as they are visible to the naked eye and do not require any specialized lighting or environment for detection. These features serve as the foundation for identifying the denomination and for clearing the first phase of authenticity verification.

However, relying solely on these low-level features does not achieve the required level of accuracy, as these elements can be easily replicated and counterfeited. To address this issue, we incorporated the detection of high-level features, which include the security thread, fiber optics, and Indian flag, and only become apparent when exposed to ultraviolet (UV) light. Including these high-level features in our research significantly enhances the authenticity verification process, as these elements are highly complex, difficult to replicate, and expensive to counterfeit. Our approach consists of two phases: Phase 1 focuses on detecting all features using the YOLO-NAS model, and Phase 2 involves verifying at least one high-level feature. This two-phase training strategy was extended by introducing an additional fusion layer for refinement. This combination ensures a robust and accurate system for identifying the denomination and authenticity of ₹500 currency notes.

3.4.1. Phase 1: Features Detection by HYOLO-NAS

In the first phase, the HYOLO-NAS model is utilized to detect and localize nine annotated features on ₹500 currency notes, as shown in Table 2. These features include low-level features visible to the naked eye and three high-level features hidden and only visible under UV light. The input to the model is an image, where the backbone part of YOLO-NAS extracts features using Eq. 1:

3.4.1.1. Backbone

$$F_l = \sigma(W_l * F_l) + B_l \qquad (1)$$

Where:
F_l : Input feature map at layer l
W_l : Convolutional weights
B_l : Bias term
σ: Activation function (ReLU).

The neck receives the backbone layer output, where the neck fuses multi-scale features from the backbone to enhance feature representation, as done in Eq. 2:

3.4.1.2. Neck

$$F_{fusion} = concat(F_{small}, F_{medium}, F_{large}) \qquad (2)$$

Where:
F_{small}, F_{medium}, F_{large}, are features extracted at different scales.
Concat: weighted sum of features.

3.4.1.3. Head

The Model gives output feature labels, bounding box coordinates, and confidence scores for each detected feature. The detection head generates objectness scores using Eq. 3, class probabilities by Eq. 4, and bounding boxes using Eq. 5:

$$P_{obj} = \sigma(S_{obj}) \qquad (3)$$

$$P_{class(c)} = \frac{exp(S_c)}{\sum_{j=1}^{k} exp(S_j)} \qquad (4)$$

$$B = (t_x, t_y, t_w, t_h) \qquad (5)$$

Where:
P_{obj}: Probability an object is in a bounding box.
$P_{class(c)}$: Class Probability for class c, where K is the sum of all the classes.
$S_{obj,\ Sc}$: Raw scores for objectness and class.
(t_x,t_y,t_w,t_h): Predicted bounding box parameters

3.4.1.4. Feature Detection Confidence

The confidence for detecting feature *i* is represented as in Eq. 6:

$$C_i = P(Feature\ \mathbf{i}\ is\ present) * IoU(Predicted\ Box, Ground\ Truth\ Box) \qquad (6)$$

Where:
P(Feature i is present): probability score output by YOLO-NAS.
IoU: Intersection over Union.

3.4.1.5. Denomination Detection

A note is classified using Eq. 7 as ₹500 if:

$$C_{500} > \tau_{denomination}\ and \sum_{j=1}^{9} 1(C_j > \tau_{low-level}) \geq K \qquad (7)$$

Where:
C_{500}: confidence score for the "500" feature.
$\tau_{denomination}$: threshold for the "500" feature confidence.
1: Indicator function (0 otherwise)

$\tau_{low\text{-}level}$: confidence threshold for low-level features.
k: A minimum number of low-level features is required to confirm the denomination.

The primary objective is to confirm the denomination by matching it with other features and then proceed to Phase 2.

3.4.2. Phase 2: Authenticity Verification

Phase 2 verifying the authenticity of the detected features of note using three high-level features: security thread, fiber optics, and the Indian flag[51)]. These features are invisible to the naked eye and only become detectable under UV light, making them difficult and costly to

Cite: P. Chhabra, S. Goyal, "A Two-Phase Deep Learning Model for Counterfeit Detection of Indian Banknotes using YOLO-NAS and UV Imaging for Visually Impaired People". Evergreen, 12 (03) 1633-1653 (2025). https://doi.org/10.5109/7388855.

replicate[50]. The presence and authenticity of features are determined based on their detection. If at least one of these high-level features is identified with a confidence score above the threshold, the note is classified as "real". Conversely, if none of these features are detected, the note is classified as "fake". Rule-based fusion combines the denomination and authenticity status, producing mixed results such as "500_real" for genuine notes or "500_fake" for counterfeits. This two-phase process ensures a robust system for detecting and verifying the authenticity of ₹500 currency notes, leveraging both visible and hidden features for accuracy and reliability. This dual-phase approach leverages low-level features for denomination recognition while relying on high-level features to strengthen authenticity verification, ensuring a robust and accurate counterfeit detection system.

3.4.2.1. Authenticity Check

Authenticity is checked using Eq. 8, where a note is classified as real if at least one high-level feature is detected with sufficient confidence:

$$max(C_{seurity\ thread}, C_{fiber\ optics}, C_{Indian\ flag}) > \tau_{authenticity} \tag{8}$$

Where,

$C_{security\ thread}$,$C_{fiber\ optics}$,$C_{Indian\ flag}$: confidence scores for the three high-level features.

$\tau_{authenticity}$: confidence threshold for high-level features.

3.4.2.2. Rule-Based Fusion Equation

This Eq. 9 shows a method that combines the results from two different classification steps in the counterfeit detection system. Specifically, it merges the denomination and authenticity results generated in separate stages into a single, unified output. The fusion is carried out through concatenation based on predefined rules, allowing the system to produce an interpretable result.

$$R_{fused-output} = D + A \tag{9}$$

Where:

D: Denomination

A: Authenticity

R: Final fused output.

3.4.2.3. Final Classification

The final classification output is determined using Eq. 10:

$$\text{Output} = \begin{cases} \text{500\_real}, & \text{if } [C_{500} \wedge ((C_{security\ thread}) \vee (C_{fiber\ optics}) \wedge (C_{Indian\ flag}))] \geq T_{high} \\ \text{500\_fake}, & \text{if if } [C_{500} \wedge ((C_{security\ thread}) \vee (C_{fiber\ optics}) \wedge (C_{Indian\ flag}))] < T_{high} \\ \text{No Denomination Detected}, & \text{otherwise} \end{cases} \tag{10}$$

3.4.3. Text-to-Speech Module

A Text-to-Speech (TTS) module was integrated into the system to provide real-time audio feedback, assisting visually impaired users. This module converts the final detection result (e.g., "500_real" or "500_fake") into speech output. The implementation uses the Google Text-to-Speech (gTTS) API, which supports multiple languages and runs efficiently on low-resource devices. Once the model predicts the denomination and authenticity of a banknote, the output string is passed to the TTS engine, which vocalises the results through the device speaker. This enables blind users to instantly receive auditory confirmation of the currency's value and authenticity.

YOLO-NAS output → Rule-Based Fusion (Denomination + Authenticity) → TTS Module → Audio Output

3.5. Flowchart

The flowchart in Figure 8 illustrates the steps for detecting counterfeit currency via a YOLO-NAS-based neural network model. Initially, an input image is processed using the YOLO-NAS framework, which identifies all important features, including both visible and invisible ones. It repeatedly optimizes the model architecture by selecting initial hyperparameters, building a child neural network, and testing it on a validation dataset..

This identifies the optimal design based on its accuracy, preserving the highest accuracy checkpoint for further testing and performance evaluation. The model further examines the identified features to determine the denomination “500” and its authenticity. In the absence of a detected denomination, the system generates a suitable notification. If a counterfeit class is detected and essential characteristics are present, the currency is designated as counterfeit ("500_fake"); otherwise, it is authentic ("500_real"). This framework further processes the final categorization results using a text-to-speech module to assist users who are blind or visually impaired.

3.6. Algorithm

```
1. Input:
 image: The image of the currency
note to be classified.
2. Load the image:
 image = load_image(input)
3. Detect features using HYOLO-NAS:

detected_features=HYOLO_NAS_model.pr
edict(image)
4. Define critical parameters:
 i. critical_features =
["security_thread", "fiber_optics",
"indian_flag"]
 ii. denomination_label = "500"
 iii. fake_class_label = "fake"
 iv. confidence_threshold = 0.8
5. Initialize flags and variables:
```

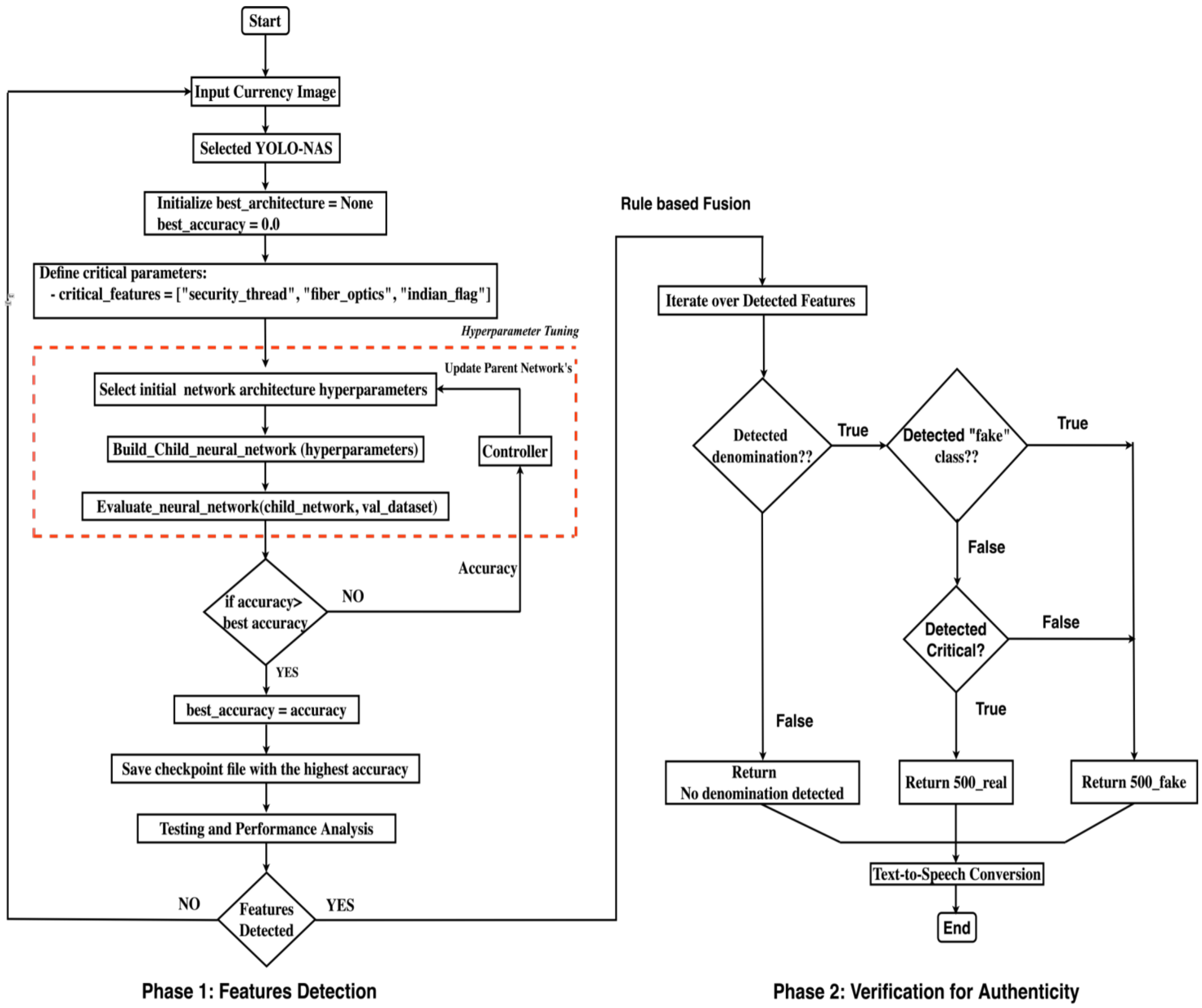


Fig. 8: Flowchart of the proposed method

```
 i. detected_critical = False
ii. detected_denomination = False
 iii. detected_fake = False
 iv. denomination = None
6. Iterate through
detected_features:
 For each feature in
detected_features:
 a. Check for critical features:
 If feature['label'] in
critical_features AND
feature['confidence'] >
confidence_threshold:
 detected_critical = True
 b. Check for denomination:
 If feature['label'] ==
denomination_label AND
feature['confidence'] >
confidence_threshold:
```

```
 detected_denomination = True
 denomination = 500
 c. Check for "fake" class:
 If feature['label'] ==
fake_class_label AND
feature['confidence'] >
confidence_threshold:
 detected_fake = True
7. Classification logic:
 a. If detected_fake is True:
 Return "500_fake"
 b. If detected_denomination is
True:
 i. If detected_critical is True:
 Return "500_real"
 ii. Else:
 Return "500_fake"
 c. If detected_denomination is
False:
 Return "No denomination detected"
```

```
8. Output:
 - The classification result:
"500_real", "500_fake", or "No
denomination detected"
```

4. Results and Discussion

In our experiment, a laptop is running Python with the following configuration for training and testing experiments: Apple M1 chip, 8 GB memory, and 245.11 GB of storage on the Macintosh HD. A self-desigend novel dataset is created where original images of the Indian 500 Rs are used. The Roboflow tool is used to create dataset[35]. The dataset is divided into training, testing, and validation.

4.1. Performance Parameters

4.1.1. Precision

The percentage of correctly detected authentic or counterfeit notes out of all notes categorized to be genuine or fake. Precision is derived by using Eq. 11.

Denomination Precision: Measures how many of the notes detected as ₹500 were correctly classified.

Authenticity Precision: Measures how many of the notes classified as real or fake were correct.

$$\mathbf{Precision} = \frac{\mathbf{True\ Positive(TP)}}{\mathbf{True\ Positive(TP) + False\ Positive(FP)}} \quad (11)$$

4.1.2. Recall

This determines the ratio of accurately recognized genuine or counterfeit notes by the system. High recall means that fewer counterfeit notes are missed by the system. Recall is derived by using Eq. 12.

Denomination Recall: Measures how many of the actual ₹500 notes were detected.

Authenticity Recall: Measures how many of the actual real or fake notes were correctly classified as real or fake.

$$\mathbf{Recall} = \frac{\mathbf{True\ Positive(TP)}}{\mathbf{True\ Positive(TP) + False\ Negative(FN)}} \quad (12)$$

4.1.3. mAP

A key metric to evaluate how well the model can predict the objects. Eq. 13 is used to calculate mAP.

$$\mathbf{mAP} = \frac{\mathbf{1}}{\mathbf{N}} \sum_{i=1}^{N} AP_i \quad (13)$$

4.1.4. F1-Score

Harmonic mean of recall and precision is calcculated by Eq. 14:

$$\mathbf{F1\_Score} = \mathbf{2} * \frac{\mathbf{Precision.Recall}}{\mathbf{Precision{+}Recall}} \quad (14)$$

4.2. Results on Indian and Thai banknotes datasets

The experiment was conducted on the Indian and Thai banknote dataset[34], with 30 epochs and a 0.0000001 learning rate using the Adam optimizer, achieving an accuracy of 90.91%. Table 3 compares various approaches, where CNN-CAM achieving the highest accuracy but requiring more epochs to converge. However, HYOLO-NAS, despite using fewer epochs and a lower learning rate, demonstrated competitive accuracy, showcasing its efficiency.

On the other hand, VGG-16 with 87.50% and VGG-19 with 85.47% also showed good results, but relying on higher epochs. In contrast, Xception (60.3%) and InceptionV3 (60.62%) had significantly lower accuracy,.

Table 3: Recognition performance comparison on Indian and Thai banknotes datasets

Methods	"Dataset of Indian and Thai banknotes with annotations"			
	Epoch	Learning rate	Optimizer	Accuracy
Vidula Meshram et al. VGG16[20]	30	0.001	RMSprop	87.50%
Vidula Meshram et al. VGG16[20]	30	0.001	RMSprop	85.47%
Vidula Meshram et al. VGG16[20]	30	0.001	RMSprop	60.31%
Vidula Meshram et al. ResNet 152V2[20]	30	0.001	RMSprop	67.81%
Vidula Meshram et al. InceptionV3[20]	30	0.001	RMSprop	60.62%
Rishabh Poojara ResNet50[19]	30	0.001	RMSprop	85%
Ahmad Nasayreh et al. CNN-CAM[15]	30	0.0001	Adam	88%
HYOLO-NAS(Our Model)	30	.0000001	Adam	90.91%

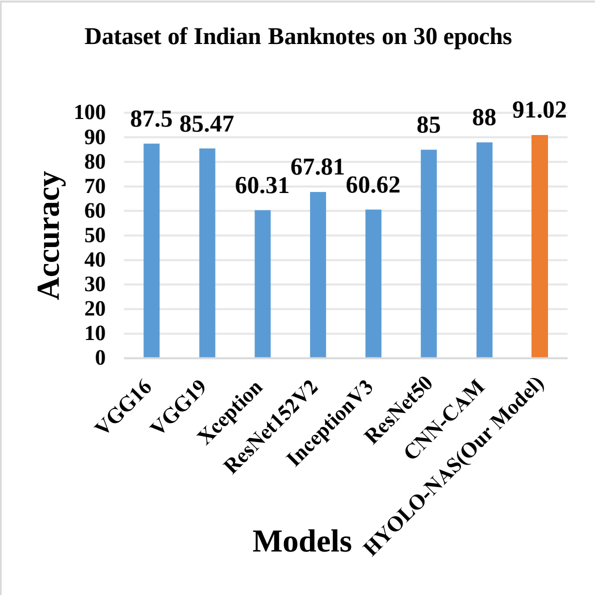
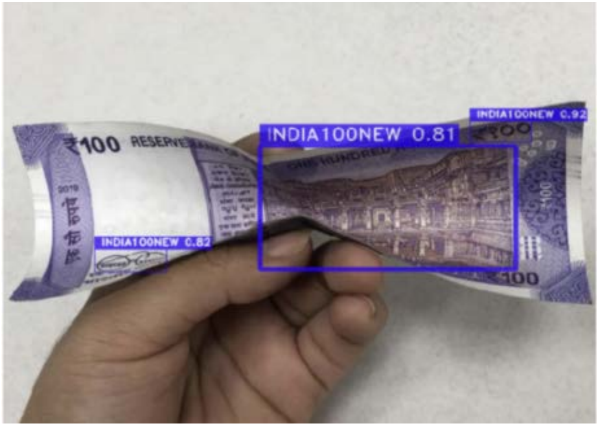


Fig. 9: Graphical representation of comparison analysis with other models

Fig. 10: Visual representation of Indian and Thai Banknote dataset

making them less suitable. Figure 9 visually represents the accuracy of each model. The Adam optimizer was used in our proposed model to boost its performance, whereas models trained with RMSprop exhibited varied accuracy. This analysis indicates that HYOLO-NAS is an effective and efficient model for banknote detection, and is also highlights the impact of hyperparameters and optimization methods on mode'l's performance.

The model was tested on folded and crumpled images, as shown in Figure 10 and successfully detected both old and new Indian currency images. Multiple instances of new 100 Rs with confidence score 0.81 and 0.92 are detected in Figure 11(a), the model successfully identified key features of old 50 Rs with confidence score of 0.72 to 0.87 as shown in Figure 11(b), new 10 Rs note is detected with high confidence score of .76 to 0.94 in Figure 11(c), the detection accuracy of 20 Rs showed mixed results in Fig 11(d), with confidene value from 0.53 to 0.75 for Mahatma Gandhi's Portrait and 0.66 for denomination.



(a) 100rs. Note

4.3. Result on custom UV-based currency dataset

The proposed HYOLO-NAS-based counterfeit detection model was trained using carefully selected hyperparameters, as shown in Table 4, to optimise performance and ensure stable convergence. A batch size of 8 was used, meaning eight images were processed in each training iteration. The input image size was fixed at 640 × 640, striking a balance between detail preservation and computational efficiency. The model was trained for

(b) 50rs. Note

(c) 10rs. Note

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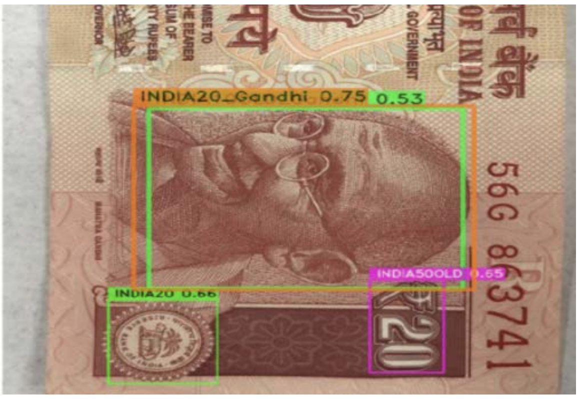


(d) 20rs. Note

Fig. 11: Visual results on Indian curreny detection

Table 4: Hyperparameter configuration for training HYOLO-NAS model

Hyper parameters	Value
Batch Size	8
Image Size	640 × 640
Initial learning rate	2e-4
Warm-up Initial LR	1e-6
Warm-up Epochs	3
Optimizer	Adam
Weight Decay	1e-4

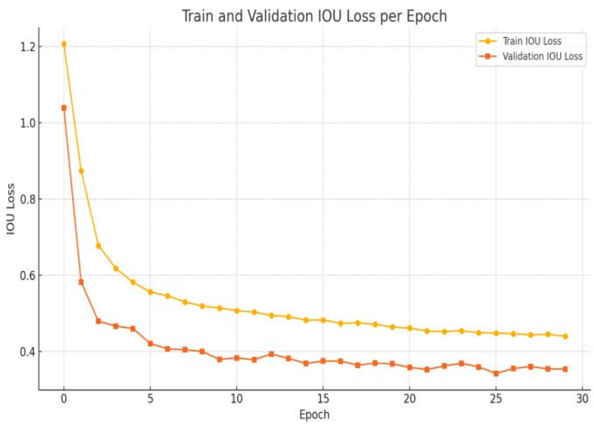


Fig. 12: Training and Validation IoU loss vs epochs

30 epochs with an initial learning rate of 2e-4, allowing it to update its weights effectively during training. A warm-up strategy was employed to prevent instability during early training, starting with a warm-up learning rate of 1e-6 for the initial 3 epochs. The training used the Adam optimiser, which is well-suited for adaptive learning and faster convergence in deep learning applications. Additionally, a weight decay of 1e-4 was applied as a regularisation technique to reduce overfitting by penalising large weight values. These hyperparameters were fine-tuned to achieve high detection accuracy while maintaining generalisation across diverse monetary samples.

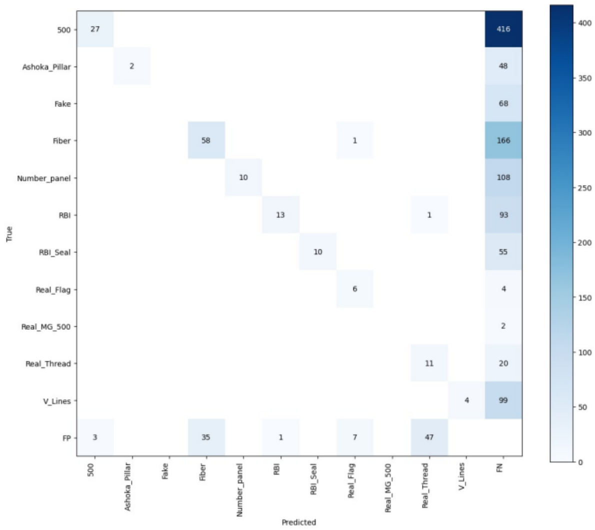


Fig. 13: Confusion matrix illustrating the classification performance of the model across currency categories

Figure 12 illustrates the variation of the Intersection over Union (IoU) loss over 30 training epochs for both the training and validation datasets, which measures the accuracy of the predicted bounding boxes in matching the actual boxes. Figure 12 demonstrates the progression of Train and Validation IOU Loss across 30 training epochs. A consistent and significant decline is observed in both curves, indicating that the model is effectively learning to improve its localization accuracy. Initially, the training IOU loss starts at approximately 1.20, while the validation IOU loss is around 1.03, reflecting high localization errors. However, by epoch 30, these values reduce to approximately 0.44 (train) and 0.35(validation), showing substantial improvement. The close alignment of the training and validation curves, without major divergence, suggests that the model generalizes well and avoids overfitting. The early epochs exhibit a steep decline, characteristic of rapid learning, while later epochs show stabilization, indicating convergence. This pattern confirms that the object detection model has been successfully optimized for accurate bounding box predictions.

Figure 13 presents the confusion matrix illustrating the performance of the proposed HYOLO-NAS-based object detection model across 11 classes representing various visible and hidden features of ₹500 currency notes, including both genuine and counterfeit indicators. The matrix quantifies the number of correct predictions (diagonal values) and misclassifications (off-diagonal values) for each class.

The model demonstrates high accuracy in detecting dominant and well-represented features such as '500' and 'Fiber', with 416 and 166 correct predictions, respectively. Other features like 'Number_panel' (108), 'RBI' (93), and 'RBI_Seal' (55) also exhibit strong recognition performance. However, some classes with fewer samples, such as 'Real_MG_500' (2) and 'Real_Flag' (4), show comparatively lower prediction counts, potentially due to class imbalance or limited visual distinctiveness in these regions.

4.3.1. Error Analysis

The presence of misclassifications is evident in off-diagonal entries. A notable observation where 35 instances of 'Ashoka_Pillar' were misclassified as 'Fiber', and a few 'RBI' instances were predicted as 'Real_Thread' or 'RBI_Seal', suggesting overlapping visual features or close spatial proximity that may confuse the model. The final row and column labeled as 'FP' (False Positives) and 'FN' (False Negatives) respectively, help summarize total classification errors. Notably, 'Fiber' and 'V_Lines' have the highest FN counts (68 and 99), indicating missed detections, likely due to their close spatial proximity and partial overlap in certain banknote layouts, especially when notes were slightly folded or degraded.

The model's overall performance shows a strong ability to distinguish major features, but there is room for improvement in minimizing false positives and enhancing detection of visually subtle or underrepresented classes. These insights highlight the importance of balanced training data, more discriminative feature extraction, and possibly employing class-specific data augmentation to improve model robustness.

4.4. Comparative results analysis on currency Dataset for counterfeiting

The comparative analysis of various deep learning models across several datasets for currency recognition is illustrated in Table 5. This reveals a clear progression in performance as more advanced architectures and richer feature sets are utilized. Early works, such as Sarangam Kodati et al. (2023), employed basic CNNs and achieved modest accuracy of 67.88%, with precision and recall both around 65%. Subsequent models, like ResNet50, VGG, and GoogleNet used by Kanawade et al. (2024) on a dataset of 1,000 Indian currency images, demonstrated significant improvements, achieving accuracies of 88%, 82%, and 80%, respectively. Similarly, Ahmad Nasayr et al.[15]) implemented CNN-CAM on 3,000 Indian and Thai banknote images, achieving 88% accuracy. Similarly, Khalid and Mammoona[22)] used YOLOv9 on 361 Pakistani currency images, obtaining 88% accuracy by focusing on deeper convolutional structures that effectively captured visible features under normal lighting. However, these approaches only contained visible features and did not incorporate hidden features such as UV-reactive elements, which are crucial for authentic counterfeit detection.

The proposed HYOLO-NAS model marks a substantial advancement by integrating both visible and hidden features, including those visible only under ultraviolet (UV) light. This dual feature approach led to a remarkable performance gain, achieving 94.43% precision, 92.71% recall, 93.78% F1-score, and 93.99% overall accuracy. HYOLO-NAS shows an improvement of 1.24% in accuracy and 1.11% in F1-score compared to the best-performing existing model, VGG-16 by Sreejit Nair et al. (2024), which reported an accuracy of 92.75%. When compared to older CNN-based approaches, the improvements are even more significant, with a gain of 26.11% in accuracy and 28.43% in precision over Sarangam Kodati's model[53)]. These results affirm that the inclusion of UV-based hidden features and the use of an optimised YOLO-NAS architecture greatly enhance the

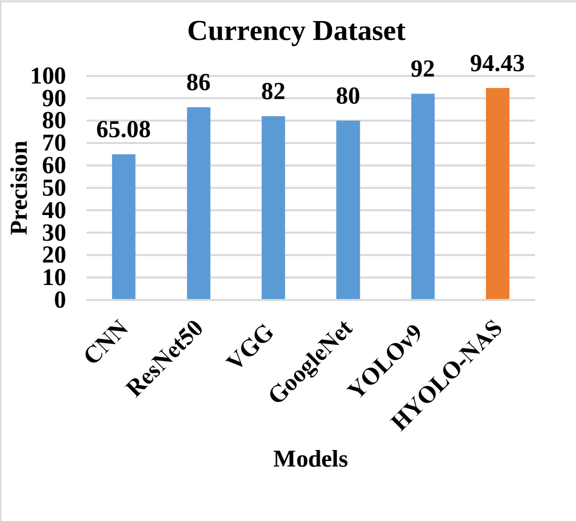
Table 5: Comparison of proposed work with existing work

Authors	Method	Images	Currency dataset							
			Precision	Recall	F1-Score	mAP	Accuracy	Visible Features	Hidden Features	Captured Images
Sarangam Kodati et al., 2023[53)]	CNN	1372 Indian Notes	65.08%	65.62%	65.35 %	-	67.88%	P	û	Normal Light
Kanawadeet al., 2024[11)]	ResNet 50	1000 Indian currency	86%	88%	87%	-	88%	P	û	Normal Light
Kanawad et al., 2024[11)]	VGG	1000 Indian currency	82%	84%	83%	-	82%	P	û	Normal Light

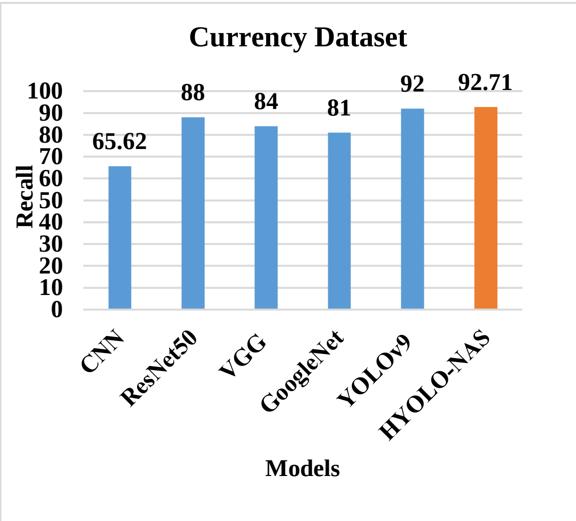
Kanawad et al., 2024[11]	Google Net	1000 Indian currency	80%	81%	80%	-	80%	P	û	Normal Light
Ahmad Nasayreh et al. 2024[15]	CNN-CAM	3000 Indian andThai banknotes	-	-	-	-	88%	P	û	Normal Light
Khalid, Mamoona, 2024[22]	YOLOv9	3611 Pakistani currency	92%	92%	92%	88%	88%	P	û	Normal Light
Sreejit Nair et al., 2024[13]	VGG-16	Self-build Indian currency	93.61%	91.71%	92.67%	-	92.75%	P	û	Normal Light
HYOLO-NAS	HYOLO-NAS	1319 Self designed Indian dataset	94.43%	92.71%	93.78%	93.78%	93.99%	P	P	UV Light

system's ability to detect counterfeit notes, making it both robust and practical for real-world applications, especially in assistive technologies for visually impaired individuals. This comparison highlights a major limitation of previous approaches: they primarily focus on denomination recognition based on visible features while neglecting hidden security elements that are crucial for counterfeit detection. In contrast, the proposed HYOLO-NAS model introduces a self-designed dataset containing 1,319 images of Indian currency captured under both normal and UV light[35]. This dataset incorporates hidden security features such as security threads, fiber optics, and fluorescence-based elements50), which significantly enhance counterfeit detection capabilities. Figure 14 shows a graphical representation where Figure 14(a) represents 94.43% precision, Figure 14(b) shows 92.71% recall, Figure 14(c) shows 93.31% F1-score, Figure 14(d) represents 93.99% accuracy and Figure 14(e) shows 93.78% mAP. The inclusion of hidden security features makes it more robust and effective in counterfeit detection, reducing the chances of false positives.

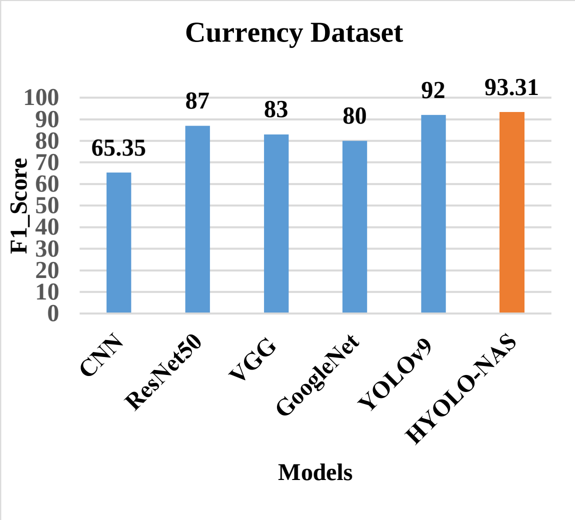
Figure 15 presents a sample of real 500 Rs notes where low-level and high-level features are detected. In Figure 15(a) and 15(b), the model detects all low-level features, including denomination, number panel and others. Additionally, it also detects "real thread" and "fiber optics" which are crucial for the second phase of the authenticity of the note. The presence of these high-level features confirms the note as "500 real". Similarly, in Figure 15(c), which depicts the backside of the note, where model detects the " 500"," real flag", and real thread. These detections indicate that the note is "500_real". Figure 16 shows the visual result of fake 500rs notes, where only low-level features are detected, while high-



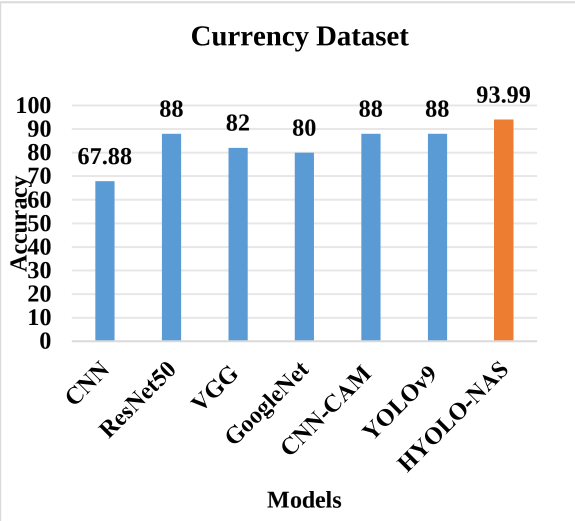
(a) Precision based comparison



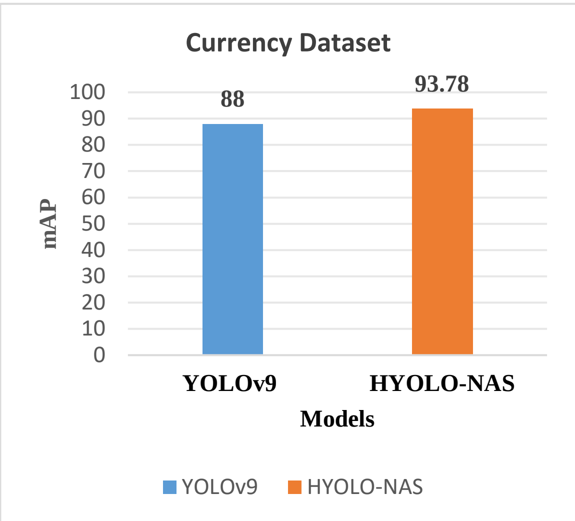
(b) Recall based comparison



(c) F1-score based comparison



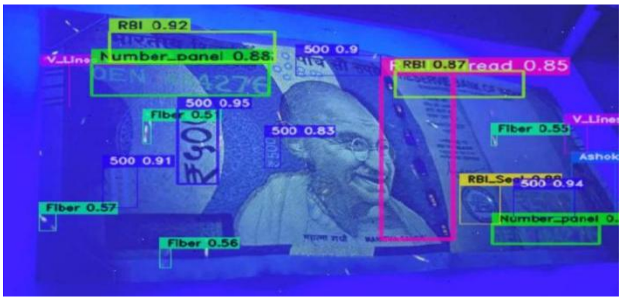
(d) Accuracy based comparison



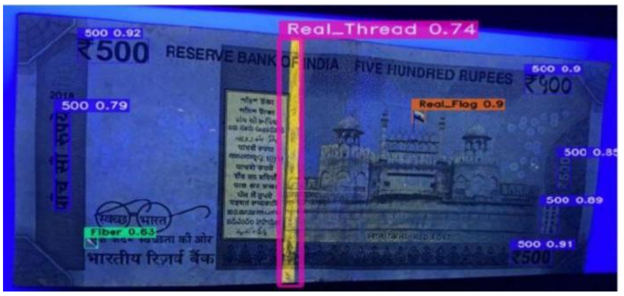
(e) mAP based comparison

Fig. 14: Result comparision based on performance parameters

level features are absent. In Figure 16(a) the model detects low-level features such as “RBI”, “RBI_seal”, Number_Panel”, and “V_lines. However, no high-level features, such as fiber or security thread are present. Figure 16(b), detects a thread, but identifies it as a fake one. In Figure 16(c) the value “500” is detected, which represents



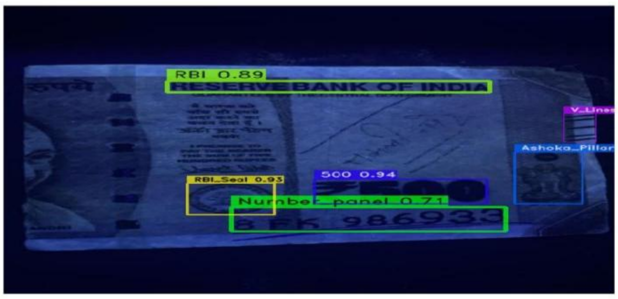
(a) Sample 2 of front view of features detection



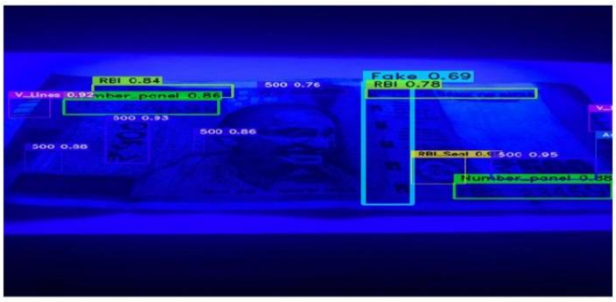
(b) Sample 1 of front view of features detection

(c) Sample 1 of back view of features detection

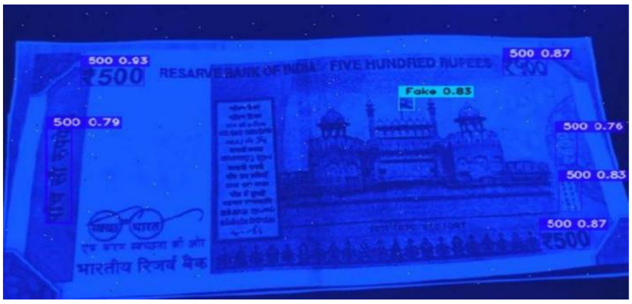
Fig. 15: Results on real Indian currency under UV light



(a) Sample 1 of front view of features detection



(b) Sample 2 of front view of features detection



(c) Sample 3 of front view of features detection

Fig. 16: Results on fake Indian currency under UV light

a low-level along with a "fake" class. This value signifies the classification of the note as "500_fake".

5. Conclusion

This study presents a robust two-phase method for counterfeit detection of Indian currency that integrates UV imaging with the HYOLO-NAS deep learning framework to enhance identification accuracy. By utilising both visible details and hidden UV-reactive security features, such as the Indian flag, fiber optics, and the security thread. The proposed system significantly enhances its reliability for detecting counterfeit currency. In the first phase, the model accurately identifies the currency denomination, while the second phase validates its authenticity using UV enhanced features. The experimental results demonstrate that this model is effective, achieving a classification accuracy of 91.02% on a combined dataset of Indian and Thai banknotes and an even higher accuracy of 93.99% on a custom UV-based dataset. These findings confirm that the proposed model outperforms traditional methods relying solely on visible features. Furthermore, the incorporation of an audio-based feedback system creates an inclusive, real-time detection framework that promotes financial independence and accessibility for individuals who are visually impaired. Overall, the proposed approach provide a secure, efficient, and socially impactful solution for authenticating real-world currency. The model is well-suited for integration into mobile applications or assistive devices, enabling visually impaired users to independently verify currency through audio-based feedback. However, practical limitations must be acknowledged. The model's dependency on proper UV illumination makes it sensitive to environmental conditions such as lighting angles and background interference.

6. Future Work

This approach can be further enhanced by incorporating additional Indian currency denominations, including newly issued notes, to improve the system's coverage and usability. Furthermore, the framework can be generalized to support other international banknotes, enabling multicurrency counterfeit detection for global financial and travel-related applications. Future work may also focus on integrating multimodal inputs, such as infrared or thermal imaging, along with UV features to enhance robustness under different environmental conditions.

Ethical and Legal Compliance

The dataset used in this study was self-collected under controlled conditions for research purposes only, with the intention of contributing to assistive technology and counterfeit detection systems. Care was taken to ensure that the collection, handling, and usage of Indian currency images including under UV lightcomplied with publicly available Reserve Bank of India (RBI) guidelines. No currency notes were defaced, tampered with, or used for illegal duplication. Furthermore, the dataset was not shared publicly to prevent misuse or violation of national currency security protocols. The research strictly adheres to ethical standards and legal boundaries, with a focus on developing a socially beneficial system for visually impaired individuals and secure transaction practices.

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