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Research Article

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Revolutionizing Currency Security: A Yolov8-Based Approach for Automated Detection of Counterfeit Nepali Banknotes

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ABSTRACT
The challenge of counterfeit currency in financial transactions requires innovative solutions for the efficient and accurate verification of banknotes. The study focuses on categorizing banknotes as fake or genuine in the context of Nepalese currency, which is crucial for maintaining economic stability, preventing financial fraud, and ensuring public trust in the monetary system. For the 180 collected samples of 1000 Nepalese rupee banknotes, the YOLOv8 algorithm achieved a true positive recall of 0.82 for the front face and 0.9863 for the back face. The mean average precision and confidence threshold achieved in the study indicate significant improvements with YOLOv8. The proposed approach demonstrates the potential for global implementation and adaptability across various hardware platforms.

Introduction
Counterfeit currency poses a significant threat to financial transactions, complicating monetary exchanges and undermining economic stability. To address this challenge, the development of advanced systems capable of distinguishing between genuine and counterfeit banknotes has become imperative [1]. This is particularly relevant in the context of Nepali currency, where the high degree of similarity between authentic and counterfeit notes makes manual verification difficult and error-prone. Automated algorithms leveraging artificial intelligence (AI) have emerged as a promising solution to enhance the accuracy and efficiency of counterfeit detection [2]. Such systems must ensure a high level of precision while automating the detection process to meet the demands of modern financial systems. The implementation of a universal system capable of accurately identifying counterfeit banknotes across different currencies could significantly reduce the proliferation of counterfeit money. This approach supports the development of image analysis-based technology that is adaptable to various currencies and hardware platforms, offering a flexible and scalable solution. By streamlining the currency verification process and minimizing human error, such technologies play a pivotal role in bolstering financial security. They not only reduce the circulation of counter feat notes but also strengthen public trust in the banking system, contributing to the overall stability and integrity of global financial transactions [3].

Security Features in Nepalese Bank Notes
The banknote incorporates various security features [4] designed to distinguish between authentic and counterfeit notes. Figure 1 shows the different security features integrated into Nepali currency. When examining the note against a bright light or when light is transmitted from the back, the shape of Laliguras is prominently visible as a watermark. Similarly, a clear image of the number “1000” can be seen holding the banknote up to the light revealing a See-Through Register. These features provide a layer of security to the banknote. A security thread is included in the banknotes adding a layer of security. If the banknote is tilted, the letters “NRB” and the number “1000” become visible. Raised Inks are present in banknotes too. They consist of areas with thicker ink which can be felt while running fingers over the banknote.

For visually impaired individuals, a Braille feature is incorporated into the note. The feature allows them to identify the note by touching the raised “M” with their fingers. Furthermore, the note employs an emboss feature, where a raised surface can be

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felt with fingers. When the banknote is tilted, the embossed area can show a metallic silver. At the back face of the note, a clear image of the number “1000” can be seen once more holding the banknote up to the light, revealing another See Through Register. Similarly, an iridescent effect can be seen while tilting the note in specific areas. This security approach combines both visual and tactile elements. As a result, these security features help in detecting counterfeit notes and stop such counterfeit attempts and better explained in Table 1.

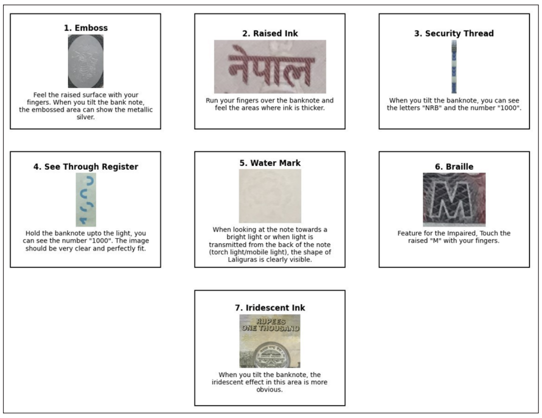

Figure 1: Security Features Front and Back Portion.

Table 1: Feature details NRs. 1000 note

Index	Type	Feature	Details
1	Feel	Emboss	Feel the raised surface with your fingers
2	Feel	Raise Inks	Glide your fingertips across the banknote to detect areas with thicker ink application.
3	Look	Security Thread	When the banknote is tilted, the letters “NRB” and the numeral “1000” become visible.
4	Look	See Through Register	When you hold the banknote up to the light, you’ll notice the number “1000” displayed clearly and precisely, fitting perfectly within the image.
5	Look	Watermark	When the note is placed under bright light or illuminated from behind with the light of a torch or mobile phone, the image of the watermark becomes visible.
6	Feel	Braille	The feature designed for individuals with impairments involves physically feeling the raised “M” with your fingertips.
7	Tilt	Iridescent Ink	When the banknote is tilted, the iridescent effect in this region becomes more pronounced.
8	Tilt	Security Thread	When you tilt the banknote vertically, the Security Thread exhibits a dynamic effect.
9	Tilt	Emboss	When the banknote is tilted, the raised section can reveal a metallic silver appearance.

Related Works

Object detection algorithms are categorized into two stage and one-stage models. Two-stage models, such as RCNN, Fast R-CNN, and Faster R-CNN, first propose regions and then classify them to improve location prediction [5]. In contrast, one-stage models like YOLO, SSD, Retina Net, Corner Net, and FCOS skip the region proposal stage, offering final localization and classification in a single step [6-11]. Among these, YOLO stands out for its real-time performance, high accuracy, and suitability for deployment on edge devices [12,13]. The YOLO network has evolved from v1 to v8, introducing features like grid division (v1), anchors (v2), multi-scale detection (v3), and advanced optimizations like SPP and GIOU loss (v4) [14]. Studies, such as one on plant disease detection, demonstrate YOLO’s versatility, with Yolov8 achieving superior accuracy compared to Yolov5 [15]. After evaluating various algorithms, our research identifies Yolov8 as the most effective solution for real-time object detection, meeting the demands of accuracy, speed, and scalability [16-19].

The authors in introduced a Raspberry Pi-based hyperspectral imaging algorithm differentiating genuine and counterfeit currency notes based on mean grey values in shorter wavelengths (400–500 nm), emphasizing portability, low cost, and efficiency with security features [20]. The paper compares the performance and inference times of DL based banknote recognition models, specifically ResNet18 using transfer learning and a custom Alex Net-type sequential CNN, finding ResNet18 achieves 100% accuracy, while the custom network demonstrates up to 6.48-times faster CPU and 16.29-times faster GPU inference times [21]. The existing counterfeit detection involves various techniques, spectral analysis ranging from classical computer vision methodologies to advanced deep learning (DL) approaches [1,22,23]. Noteworthy contributions include proposals leveraging CNNs for banknote recognition, such as transfer learning with Histograms of Oriente Gradients for Euro banknotes and using the SIFT algorithm, a Yolo8 net for Mexican banknotes, and custom CNN architectures for various international currencies [24-27]. The paper presents a rapid and effective algorithm for classifying multinational banknote images based on size information and multi-template correlation matching, achieving 100% classification accuracy for unsoiled bank notes and 99.8%accuracy for soiled banknotes, with an average processing time of approximately 4.83 MS per banknote [28]. The visually impaired face significant challenges in currency transactions, as features like embossing on banknotes are often ineffective due to the worn condition of circulated currency. To address this, Surya et al. integrated ML with the YOLOv8 algorithm for precise currency denomination detection, enhancing independence for visually impaired individuals [29]. Performance testing of the device, which achieved a 99% average accuracy, demonstrates its effectiveness in real-time recognition of Indonesian Rupiah denominations, even under varying conditions such as object rotation and contrast changes. Goma et al. investigated counterfeit detection for Philippine Php 500 and Php 1000 banknotes using a combination of MobileNetv2 and YOLOv5s with transfer learning [30]. Their study compared MobileNetv2, achieving mAP scores of 92.8% and 93% for Php 500 and Php 1000, respectively, against ResNet-18, which achieved higher mAP scores of 93.6% and 95% but required more computational resources. This research highlights the potential of lightweight models like Mobile Netv 2 for efficient counterfeit detection in the Philippine banking system.

Materials and Methods

Data Collection

We collected samples of both counterfeit and genuine 1000 Nepalese rupee notes, focusing on minimizing image variability by using a mobile phone to capture photographs of both the front and back for use in a mobile application. The dataset comprised 180 samples each of fake and real notes for training, with 20 samples reserved for testing. The authenticity of the notes was verified by the Government of Nepal (GON). Images were captured at 4032x3024 pixels with a focal length of 3.99mm and an aperture value of focal length/1.7 using an iPhone 7.

Preprocessing

Automatic Algorithm

Algorithm 1 Algorithm: Automated Cropping

Input: Input image *I*, Template image *T*
Output: Cropped region saved as output image

1: Convert *I* and *T* to grayscale:

I_g = grayscale(I), T_g = grayscale(T)

2: Get dimensions of the template T_g:

(w_T, h_T) = dimensions(T_g)

3: Perform Template Matching Using Normalized Cross Correlation

$$R(x,y) = \frac{1}{(w_T, h_T)\,\sigma I_g\,\sigma T_g} \sum_{i=0}^{w_T-1} \sum_{j=0}^{h_T-1} (I_g(x+i, y+j) - \mu I_g) \cdot \lambda$$

Where:
$\lambda = T_g(i,j) - \mu T_g$

4: Find the location of the best match:

$$(x_{max}, y_{max}) = \arg\max_{(x,y)} R(x,y)$$

5: Define the top-left and bottom-right corners of the cropped region:

top_left = (x_{max}, y_{max})
bottom_right = $(x_{max} + w_T, y_{max} + h_T)$

6: Extract the region from I:

cropped_region = $\mathbf{I}[y_{max} : y_{max} + h_T, x_{max} : x_{max} + w_T]$

7: Save the cropped region as an output image.

An automated image cropping algorithm was developed using Algorithm 1, visually explained in Figure 2, designed to extract the informative portions of each note. Given that each banknote features distinct front and back sections, the algorithm effectively removes the background, retaining only the relevant details when captured with a mobile phone.

The algorithm begins by converting both the input image *I* and template image *T* to grayscale, producing I_g and T_g, respectively. Template matching is then performed using normalized cross-correlation, where the matching score R(x,y) is computed using Equation 1.

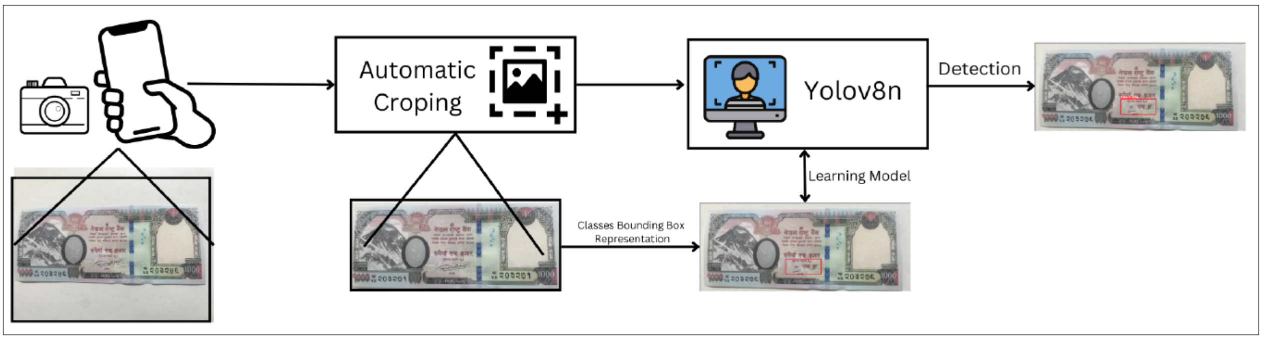

Figure 2: Steps in automatic cropping of an image

$$R(x,y) = \frac{1}{(w_T, h_T)\,\sigma I_g\,\sigma T_g} \sum_{i=0}^{w_T-1} \sum_{j=0}^{h_T-1} (I_g(x+i, y+j) - \mu I_g) \cdot \lambda \quad (1)$$

where $\lambda = T_g(i,j) - \mu T_g$ The location of the best match is identified by Equation 3.

$$(x_{max}, y_{max}) = \arg\max_{(x,y)} R(x,y) \quad (2)$$

Finally, the cropped region is extracted from the input image *I* using the coordinates of the best match as per Equation 6, and the result is shown in Figure 3. The VGG annotation of the image is shown in Figure 11.

$$\text{cropped\_region} = \mathbf{I}[y_{max} : y_{max} + h_T, x_{max} : x_{max} + w_T] \quad (3)$$

Model Training

Environmental Setup

The experiments forth is study were conducted on Google Collab with a T4 GPU, providing GPU acceleration for efficient model training. The software stack utilized includes the Linux-based operating system of Google Collab and the ultralytics framework, which is ideal for implementing and training YOLOv8 models with GPU support. This setup ensures optimal performance for deep learning tasks.

Performance Evaluation Metrics

Mean Average Precision (mAP)

The mean average precision is the average of precision values at different recall levels. It provides a consolidated measure of the model's performance across various detection thresholds.

$$\text{mAP} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{AP}_i \quad (3)$$

Average Precision (AP)
The average precision is the area under the precision recall curve, representing the precision at different recall levels. AP is computed for each class and then averaged to calculate mAP.

$$\text{AP}= \int_0^1 \text{precision(r) dr} \quad (5)$$

Precision and Recall
Precision is the ratio of true positive predictions to the total predicted positives as shown in Equation 6. Recall is the ratio of true positive predictions to the total actual positives as shown in Equation 7

$$\text{P}=\frac{\text{TP}}{\text{TP+FP}} \quad (6)$$

$$\text{R}=\frac{\text{TP}}{\text{TP+FN}} \quad (7)$$

Here, TP denotes true positives, FP denotes false positives, and FN denotes false negatives

Model Selection
The collected data was split into a 90:10 ratio for training and testing, respectively. The model was trained on 90% of the data and evaluated on the remaining 10%. We utilized the ResNet50v2 and Mobile Net models. In the experimental setup using categorical cross-entropy, the MobileNetV2 model achieved a training F1 score of 0.87 and a validation F1 score of 0.37 after 20 epochs. However, upon testing with individual image instances, the model failed to generalize well to the data. It also exhibited overfitting on the back portion of the notes and underfitting on the front portion.

A detailed analysis of the model's layers revealed that the gradient primarily follows the compact, feature-rich regions of the notes, rather than the fake portions. As shown in Figure 5, the decision-making process is most influenced by these compact areas of the images. The image gradient analysis indicates that the model is overfitting the dataset. For feature extraction, we employed ResNetv2 to extract features from the images, followed by the application of various machine learning models, using an SVC head for image classification into four categories: Front Fake, Front Genuine, Back Fake, and Back Genuine. The model achieved an accuracy of 0.6, and the classification report revealed a bias towards the back portion of the images. This insight motivated us to explore an image segmentation-based transfer learning model to better handle these low resource datasets.

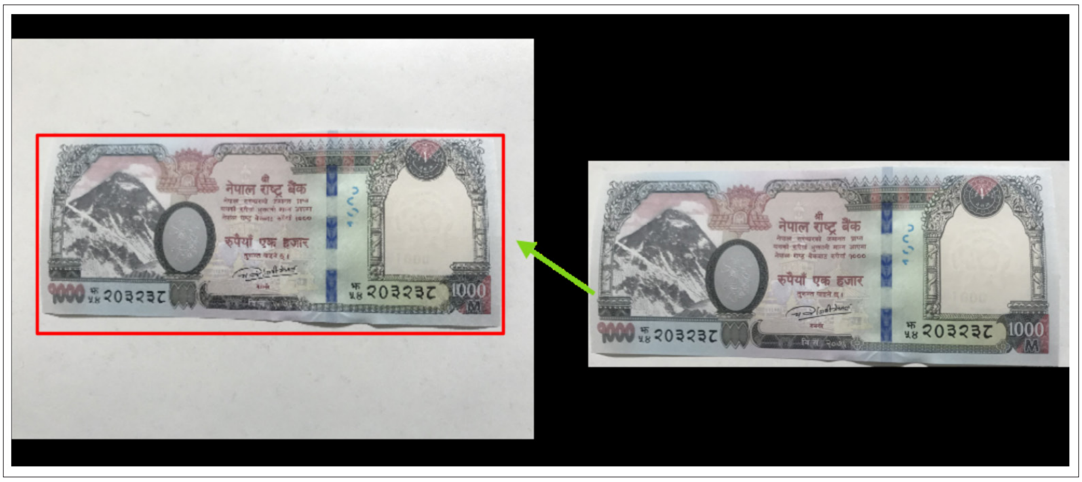

Figure 3: Cropped images after applying the automatic process.

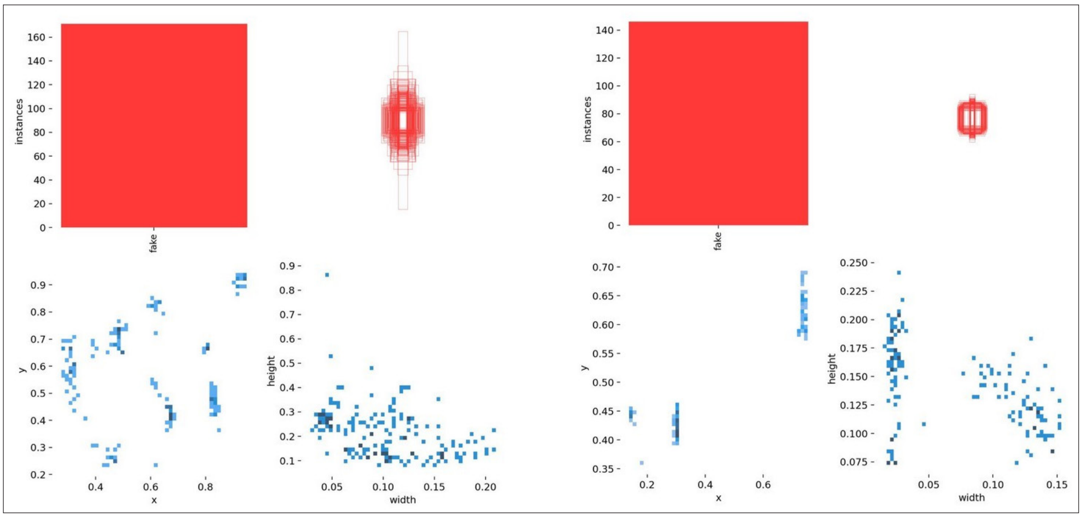

Figure 4: Cropped images are annotated using the VGG annotator

Yolov For this task, we chose the Yolov8 nano model for8 segmentation-based classification. The data was created using the VGG annotation tool, and we normalized the annotations to match the size of the images. Various augmentations were applied, including translation, scaling, shearing, perspective changes, mosaic flipping, and others. After 50 iterations, both models converged. We trained two custom models for the front and back portions of the images, with the front-face model achieving a true positive recall of 0.82456, and the back model reaching a true positive recall of 0.9863. The detailed training report for Yolov8 is shown in Figure 6.

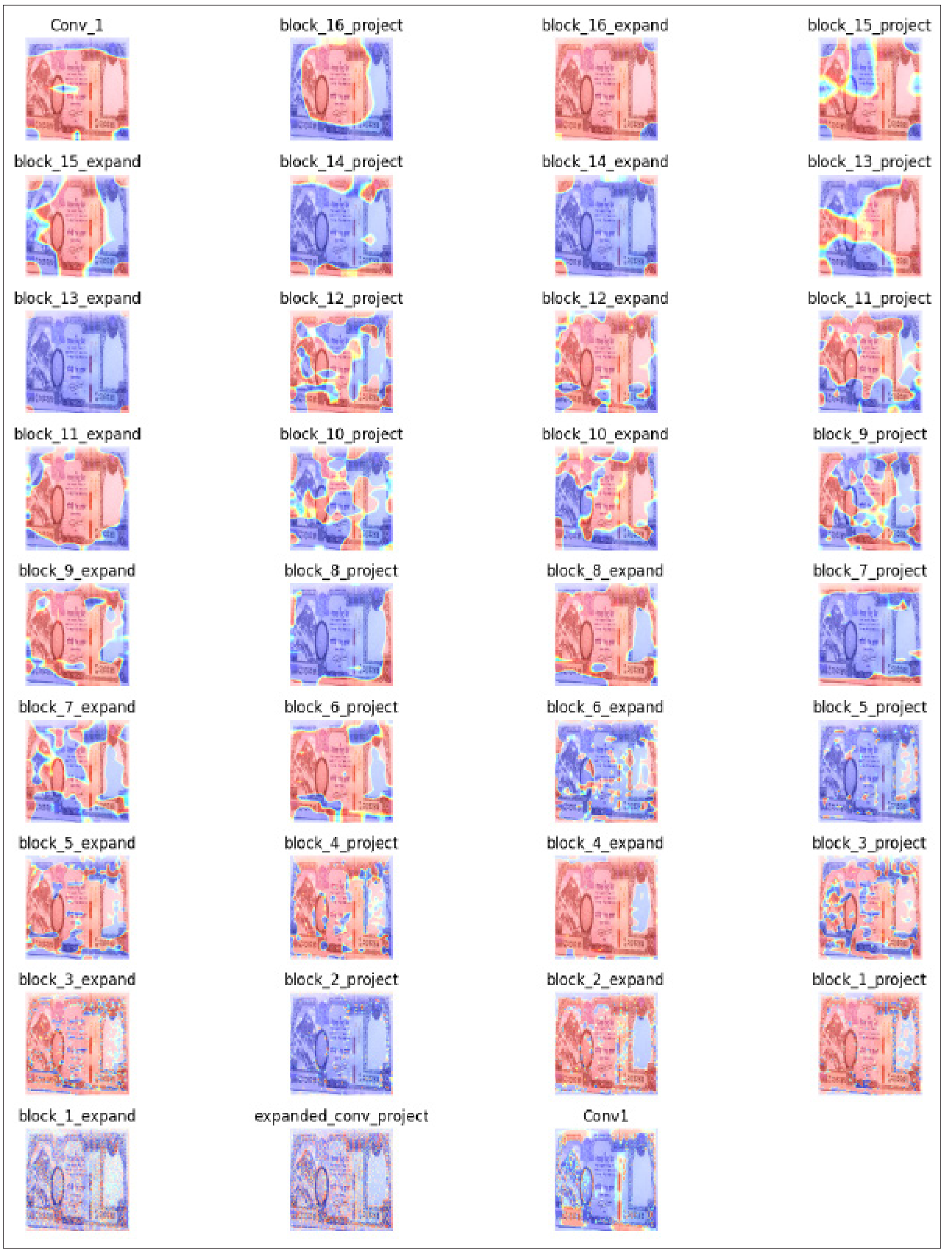

Figure 5: Image Gradient

Yolov To validate our approach, we compared different models, 5 including training the Yolov5 small model with the same dataset and experimental setup. Our findings indicate that the segmentation-based approach is effective for this task, particularly when distinguishing between fake and genuine images with subtle feature differences. Image segmentation, which divides an image into multiple regions based on characteristics like color, texture, or light intensity, enhances the robustness of fake and genuine image recognition. The detailed training report for Yolov5 is shown in Figure 7.

The results show that Yolov8 outperforms Yolov5 in terms of mAP at both IOU thresholds of 0.5 and 0.95 for both the front and back portions of the note (shown in Figure 8. This indicates that Yolov8 has better overall detection performance compared to Yolov5 in this scenario. The output for the front face is shown in Figure 9 and back face is shown in Figure 10.

Statistical Analysis

To compare the performance of the Yolov8 and Yolov5 models, we conducted a chi-square test using a sample of 20 images. These images contained a total of 51 fake regions. The Yolov8 model predicted 21 regions as fake and 20 as not fake, while the Yolov5 model identified all 51 regions as fake, achieving 100% accuracy for this sample. However, Yolov8 demonstrated higher precision in feature detection by accurately identifying only the fake portions, making it more reliable for precise authenticity verification.

Statistical Validation Using Chi-Square Test

To provide statistical proof of the performance differences between Yolov5 and Yolov8, we applied the Chi Square Test for Independence. This test helps determine if the observed differences in predictions are statistically significant.

Contingency Table

The confusion matrices for both models were used to. create the following contingency table:

	TP (Fake)	FN (Not Fake)
Yolov5	51	0
Yolov8	21	20

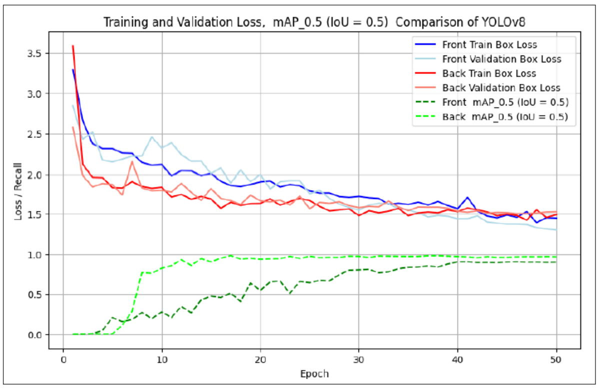

Figure 6: Yolov8 Training and Validation loss

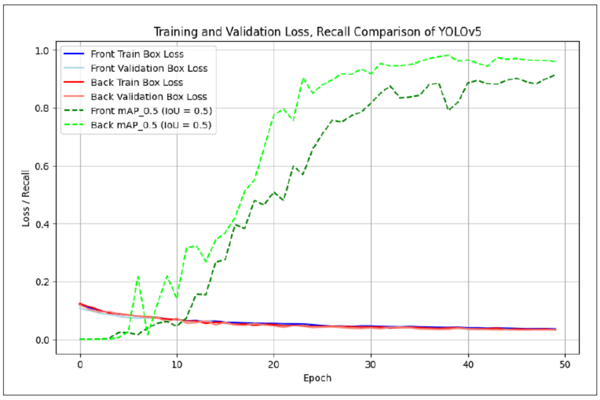

Figure 7: Yolov5 Training and Validation loss

Chi-Square Test Results

Based on the contingency table, the following results were obtained:

- **Chi-Square Statistic (x^2):** 28.99
- **P-value:** 7.29e-08
- **Degrees of Freedom:** 1

The expected frequencies for the Chi-Square Test are as follows:

	TP (Fake)	FN (Not Fake)
Yolov5	39.91	11.09
Yolov8	32.09	8.91

The chi-square test reveals a significant difference in the performance of Yolov5 and Yolov8 ($p < 0.05$). While Yolov5 achieves 100% accuracy for identifying fake regions, it lacks precision as it detects all regions as fake. In contrast, Yolov8 demonstrates superior precision by correctly identifying only the fake portions, making it more suitable for tasks requiring detailed feature detection.

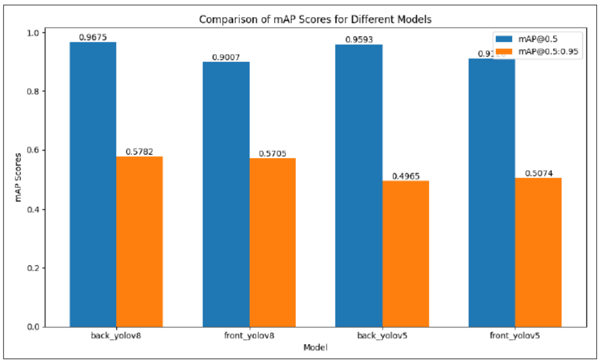

Figure 8: Comparison of mAP scores for different models

Figure 9: Output Images for front face

Figure 10: Output Images for back face

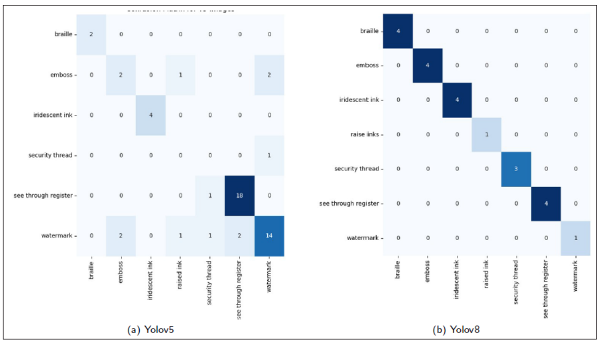

Figure 11: Confusion Matrix

Interpretation

The p-value in our analysis is much smaller than the. commonly used threshold of 0.05, which indicates that the difference in performance between models v5 and v8 in predicting fake images is statistically significant. In other words, this low p-value strongly suggests that the observed performance difference is unlikely to have occurred by chance. Additionally, the high chi-square statistic reinforces this finding by quantifying a substantial difference between the models. Together, these metrics provide strong evidence that models v5 and v8 perform differently when it comes to identifying fake images.

The statistical test confirms that model v5 and model v8 perform significantly differently in predicting fake images. Specifically, model v5 shows superior performance in detecting fake images compared to model v8.

Limitation

The study focuses on identifying fake notes by analyzing their images. To do this, we've trained our model to detect eight specific features on the notes. However, fake notes often have more than eight distinguishing features, and our model might miss some of them. We use YOLO image models for this task, which are excellent for visual analysis but can't feel the texture or surface of the notes. This means certain security features, like the texture or the use of iridescent ink (which reflects yellow light when tilted), are difficult to detect with our approach. Similarly, features like the "see-through register," which can only be verified by holding the note up to a light source, can't be analyzed accurately. While our method is powerful, it highlights the limitations of relying solely on image-based technology for tasks that sometimes require touch or specialized conditions to verify authenticity.

Conclusion

This study addresses a critical gap in counterfeit currency detection, focusing on the unique characteristics of Nepali banknotes. Through extensive experiments in image classification, we conclude that image segmentation, particularly with the Yolov8 model, is the most effective approach for detecting counterfeit currency. Yolov8's advanced features were instrumental in developing a reliable system for automating counterfeit detection. Transitioning from traditional classification methods to segmentation has enabled the identification of subtle details on banknotes, significantly improving detection accuracy. The model's strong performance, as demonstrated by high mAP scores, highlights its potential for real-world financial applications. Additionally, our proposed methodology offers a general framework for analyzing counterfeit currency, contributing to efforts in mitigating the issue of fake money.

However, the system's accuracy is influenced by various factors, including lighting conditions, variations in note designs, and evolving counterfeit production techniques. Future research will focus on fine-tuning the model to address these challenges and expanding its applicability to currency verification beyond Nepal, enhancing its utility on a global scale.

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