International Journal of Innovative Research in Computer Science and Technology (IJIRCST)
ISSN(Online): 2347-5552, Volume-12, Issue-2, March 2024
https://doi.org/10.55524/ijircst.2024.12.2.1
Article ID IRP1429, Pages 10-20
www.ijircst.org

Enhanced Counterfeit Detection of Bangladesh Currency through Convolutional Neural Networks: A Deep Learning Approach

Abhijit Pathak[1], Arnab Chakraborty[2], Minhajur Rahaman[3], Taiyaba Shadaka Rafa[4], and Ummay Nayema[5]

[1]Assistant Professor, Department of Computer Science and Engineering, BGC Trust University Bangladesh, Chattogram, Bangladesh
[2,3,4,5] Student, Department of Computer Science and Engineering, BGC Trust University Bangladesh, Chattogram, Bangladesh

Correspondence should be addressed to Abhijit Pathak; abhijitpathak@bgctub.ac.bd

Received 14 February 2024; Revised 27 February 2024; Accepted 7 March 2024

ABSTRACT- Counterfeiting poses a significant threat to the stability of Bangladesh's currency, the Taka, necessitating advanced methods for detection and prevention. This paper presents an innovative approach to counterfeit detection using Convolutional Neural Networks (CNNs), a deep learning technology. Explicitly focused on Bangladesh's currency, this method aims to enhance the accuracy and efficiency of counterfeit detection by leveraging the power of artificial intelligence. The proposed approach involves training CNNs on a dataset of authentic and counterfeit Bangladeshi currency images, allowing the network to learn intricate features and patterns indicative of counterfeit notes. By exploiting the hierarchical structure of CNNs, the system can automatically extract discriminative features from currency images, enabling robust detection of counterfeit banknotes. The CNN-based approach offers several advantages compared to traditional methods, which often rely on manual inspection or rule-based algorithms. It can handle complex visual information more accurately and efficiently, making it well-suited for detecting subtle counterfeit features.

Furthermore, the adaptability of CNNs allows for continuous learning and improvement, ensuring resilience against evolving counterfeit techniques. The efficacy of the proposed method is validated through extensive experimentation and evaluation, demonstrating its superior performance in detecting counterfeit Bangladesh currency notes. By harnessing the capabilities of deep learning, this approach not only enhances the security of Bangladesh's financial system but also serves as a scalable solution applicable to other currencies and regions facing similar challenges. In conclusion, the integration of Convolutional Neural Networks represents a significant advancement in counterfeit detection technology, offering a powerful and versatile tool for safeguarding the integrity of Bangladesh's currency and combating financial fraud on a global scale.

KEYWORDS- Bangladesh Currency, Image Processing, Counterfeit Detection, Deep Learning, Machine Learning.

I. INTRODUCTION

Counterfeiting of currency presents a persistent challenge to Bangladesh's economic stability and security, with the integrity of the Taka, the national currency, constantly under threat. Despite efforts by regulatory authorities such as the Bangladesh Bank, counterfeit currency continues circulating in the market, undermining trust in financial transactions and eroding public confidence. In response to this pressing issue, this research introduces a state-of-the-art approach to counterfeit detection using Convolutional Neural Networks (CNNs), a form of deep learning technology. By harnessing the power of artificial intelligence, specifically tailored to Bangladesh's currency, this novel method aims to revolutionize counterfeit detection by automating the process and significantly enhancing accuracy. Traditional counterfeit detection methods often rely on manual inspection or rule-based algorithms, which are limited in detecting sophisticated counterfeit features.

In contrast, CNNs offer a data-driven approach that can automatically learn and extract complex patterns from currency images, enabling more robust and efficient detection of counterfeit banknotes. The motivation for adopting CNNs stems from their proven success in various computer vision tasks, including image classification and object detection. By training CNNs on a dataset of authentic and counterfeit Bangladeshi currency images, this research seeks to leverage the network's inherent ability to discern subtle visual cues indicative of counterfeit notes. The objectives of this research are twofold: to develop a CNN-based counterfeit detection system tailored explicitly to Bangladesh's currency and to evaluate its accuracy, efficiency, and scalability performance. Through systematic experimentation and evaluation, this research aims to demonstrate the efficacy of CNNs in enhancing the security of Bangladesh's financial system and mitigating the risks associated with counterfeit currency.

In summary, integrating Convolutional Neural Networks represents a significant leap forward in counterfeit detection technology, offering a sophisticated and adaptable solution to the persistent problem of counterfeit currency in

Bangladesh and beyond. By leveraging deep learning capabilities, this research seeks to empower regulatory authorities, financial institutions, and the general public with the tools needed to combat financial fraud and safeguard the integrity of the nation's currency. The necessity of combating counterfeit currency in Bangladesh cannot be overstated, given its detrimental impact on economic stability and public trust in financial institutions. With the Bangladesh Bank as the sole authority responsible for currency issuance and regulation, ensuring the authenticity of the Taka is paramount to maintaining the integrity of the country's financial system. Motivated by the urgency of addressing this challenge, this research proposes a cutting-edge approach to counterfeit detection by utilizing Convolutional Neural Networks (CNNs). CNNs, inspired by the structure of the human visual system, excel in extracting intricate patterns and features from complex images, making them well-suited for tasks such as currency verification. The decision to focus on CNNs arises from their proven effectiveness in various domains, including image classification, object detection, and pattern recognition. By leveraging the inherent capabilities of CNNs, this research aims to develop a sophisticated counterfeit detection system capable of discerning subtle discrepancies between genuine and counterfeit Bangladeshi currency notes. Traditional methods of counterfeit detection, relying on manual inspection or simplistic algorithms, often struggle to keep pace with the evolving sophistication of counterfeiters.

In contrast, CNNs offer a data-driven approach that can adapt and learn from vast amounts of currency image data, enabling more accurate and reliable detection of counterfeit banknotes. Through systematic experimentation and evaluation, this research seeks to demonstrate the superiority of CNN-based counterfeit detection over conventional methods in accuracy, efficiency, and scalability. By harnessing the power of deep learning, this research provides a transformative solution to the persistent problem of counterfeit currency in Bangladesh, bolstering confidence in the financial system and safeguarding the interests of individuals and institutions alike. In summary, adopting Convolutional Neural Networks represents a paradigm shift in counterfeit detection technology, offering a potent tool for combating financial fraud and preserving the integrity of Bangladesh's currency. Through collaborative efforts between academia, industry, and regulatory authorities, this research aims to pave the way for a more secure and resilient financial ecosystem, resilient to the threats posed by counterfeit currency.

II. RELATED WORKS

Wang et al., as discussed by the authors, proposed a deep learning-based counterfeit currency detection system that uses convolutional neural networks (CNNs) for feature extraction and classification, which can be integrated into various automated teller machines (ATMs) and vending machines to detect counterfeit money in real-time. The provided paper does not mention "Bangladesh Currency" or "Enhanced Counterfeit Detection" using Convolutional Neural Networks. The paper discusses general counterfeit detection using deep learning techniques [1]. In this article, a Convolutional Neural Network (CNN) model was proposed for detecting fake currency notes. The experimental results validate that the proposed model effectively recognizes authentic and counterfeit currencies of various denominations with the confidence score. The provided paper is not about the enhanced counterfeit detection of Bangladesh currency through Convolutional Neural Networks [2]. The provided paper discusses the development of a software solution for detecting fake Bangladeshi banknotes using Convolutional Neural Networks (CNN) and other algorithms. In this paper, the authors used Convolutional Neural Network (CNN) and FLANN-based Matcher with the Scale-Invariant Feature Transform (SIFT) algorithms for detecting fake Bangladeshi banknotes [3].

The provided paper is about a deep learning approach for detecting counterfeit Bangladeshi currency using Modified AlexNet and Multi Support Vector Machine (M-SVM). In this paper, the Modified AlexNet (M-AlexNet) was used for feature extraction from BANGLADESHI BANKNOTE, where classification is followed by a support Vector Machine (SVM) [4]. The provided paper does not discuss "Enhanced Counterfeit Detection of Bangladesh Currency through Convolutional Neural Networks: A Deep Learning Approach." In this article, a support vector machine (SVM) was used to classify bank notes as authentic or counterfeit using the data retrieved from the photos of the bank notes; SVM performs better overall and is more effective in pattern categorization [5]. The provided paper is about the automatic detection and recognition of Bangladeshi banknotes using lightweight CNN architectures and transfer learning. It does not mention enhanced counterfeit detection or the use of convolutional neural networks for this purpose. This paper's authors presented their experiments on several state-of-the-art deep learning methods based on Lightweight Convolutional Neural Network architectures combined with transfer learning [6]. The provided paper is about using deep learning approaches for the automated detection of counterfeit Indian banknotes. It does not mention anything about the detection of counterfeit Bangladesh currency. In this paper, the use of CNNs and RNNs is proposed to detect counterfeit currency notes to enhance the security of banknotes and protect against counterfeiting, which outperforms traditional detection methods in terms of accuracy and precision [7]. The provided paper is about real-time fake note detection using a deep convolutional neural network. The paper does not mention enhanced counterfeit detection of Bangladesh currency or a deep learning approach. This article used a deep convolutional neural network to detect counterfeit currency through the mobile application, which was tested using real-time images captured through the smartphone camera [8].

Based on the literature reviews provided, it's evident that several studies have explored the application of deep learning techniques, including Convolutional Neural Networks (CNNs), for counterfeit currency detection. However, none of the referenced papers specifically address the topic of "Enhanced Counterfeit Detection of Bangladesh Currency through Convolutional Neural Networks: A Deep Learning Approach," as proposed in this article. Wang et al. [1] proposed a CNN-based counterfeit currency detection system applicable to various automated machines, but the study does not focus on Bangladesh currency or enhanced counterfeit detection. Similarly, while other studies [2-8] discuss using deep learning techniques for counterfeit currency detection, they do not specifically target Bangladesh currency or emphasize enhanced counterfeit detection through CNNs. The absence of literature directly addressing the proposed topic underscores the need for this research. This study aims to fill this gap in the literature by targeting Bangladesh currency and employing advanced CNN-based approaches. It seeks to develop a tailored solution for detecting counterfeit Bangladeshi banknotes using state-of-the-art deep learning techniques, ultimately contributing to the advancement of counterfeit detection technology in Bangladesh currency. Given the absence of literature directly addressing the proposed topic, it's clear that there is a significant gap in research focusing on the enhanced counterfeit detection of Bangladesh currency through Convolutional Neural Networks (CNNs). While existing studies have explored deep learning techniques for counterfeit currency detection, they do not specifically target the unique characteristics and challenges of detecting counterfeit Bangladeshi banknotes. The lack of attention to this specific problem highlights the need for specialized research efforts tailored to the context of the Bangladesh currency. Such endeavors could lead to the development of more effective and accurate counterfeit detection systems designed to address the challenges posed by counterfeit Bangladeshi banknotes. This research aims to pioneer a new direction in counterfeit detection by focusing on Bangladesh currency and leveraging advanced CNN-based approaches. Through systematic experimentation and evaluation, it seeks to demonstrate the feasibility and efficacy of using CNNs for enhanced counterfeit detection of Bangladesh currency, ultimately contributing to advancing security measures in the country's financial system.

III. METHODOLOGY

The proposed CNN model, depicted in Figure 1, has demonstrated exceptional efficacy in identifying counterfeit Bangladesh currency denominations, specifically BDT 100. This three-layered model incorporates various methods, such as edge detection, image segmentation, and filtering, to enhance its reliability. Currency characteristics are integrated into the model to bolster its performance further, ensuring a comprehensive approach to counterfeit detection [9].

The Deep Convnet is trained on a Bangladeshi banknotes dataset, allowing it to learn and recognize the distinct features indicative of genuine and counterfeit currency. Leveraging Deep CNN techniques, the model is programmed to process input images efficiently, delivering accurate results in real time. Moreover, including a user-friendly web interface, as illustrated in Figure 6, enables seamless image uploads for analysis and immediate feedback on the authenticity of the currency [10].

Following this systematic approach, the proposed CNN model offers a robust and efficient solution for counterfeit detection of Bangladesh currency. Its integration of advanced techniques and user-friendly interface ensures accessibility and reliability, making it a valuable tool for safeguarding against financial fraud.

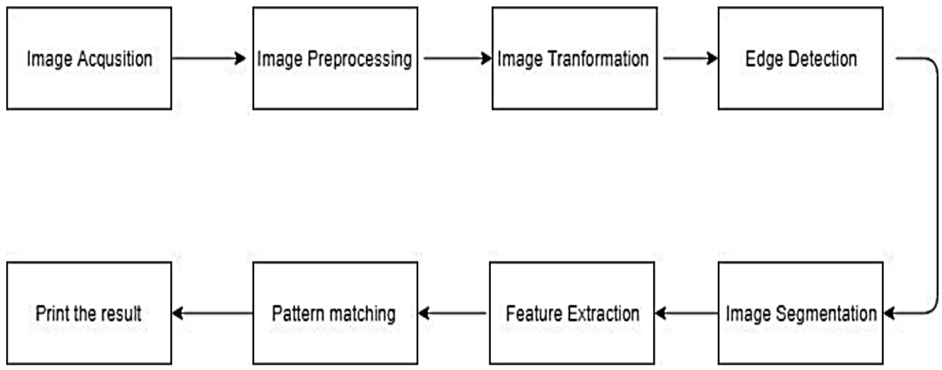

Figure 1: Flow diagram of the proposed model Deep Convnet

In the proposed model for identifying counterfeit Indian currency notes, Convolutional Neural Networks (CNNs) are crucial in enhancing image resolution and facilitating detection. The authors employed a Deep CNN architecture comprising three Convolutional layers, as illustrated in Figure 2. Additionally, two fully connected layers were utilized for classification, enabling the model to determine the probability of the currency note being either fake or original [11].

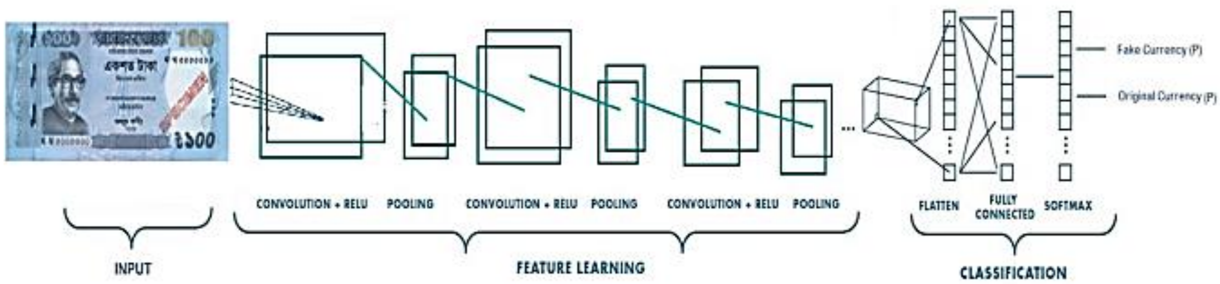

Figure 2: Identifying Counterfeit Currency Note Tk. 100 using Deep ConvNet

CNNs are well-suited for tasks involving image analysis and classification due to their ability to learn and extract meaningful features from input images automatically. The convolutional layers in the model apply filters to the input image, capturing spatial patterns and enhancing resolution through feature extraction. This process enables the model to discern subtle details and distinguish between genuine and counterfeit currency notes. Furthermore, the fully connected layers in the model integrate the extracted features and make high-level predictions regarding the authenticity of the currency note. By leveraging the hierarchical structure of CNNs and the power of deep learning, the proposed model can effectively classify Indian currency notes with high accuracy[12].

Overall, using CNNs in the proposed model enhances image resolution and enables robust counterfeit detection by leveraging advanced machine-learning techniques. Through the integration of deep learning algorithms, the model can contribute significantly to the prevention of financial fraud and the maintenance of currency security.

A. Security features of Tk. 100 extracted from the banknote images

- **Watermark:** The paper mentions the extraction of watermarks as a security feature for identifying counterfeit banknotes. Process for extracting watermarks from banknote images: Watermarks are extracted as one of the security features in the paper for identifying counterfeit banknotes. The provided sources do not mention the specific process for extracting watermarks from banknote images. However, extracting watermarks from images generally involves enhancement, filtering, and segmentation techniques. Image enhancement techniques can be used to improve the visibility and clarity of the watermark. Filtering techniques can be applied to remove noise and enhance the contrast of the watermark. Segmentation techniques can separate the watermark region from the rest of the image. Advanced algorithms and methods, such as frequency domain analysis or machine learning techniques, may also be employed for more accurate and robust watermark extraction [13].
- **Uneven printing:** Uneven printing is another security feature extracted from the acquired banknote images. Specific image processing techniques used for detecting uneven printing: The provided sources do not mention the methods used for detecting uneven printing in banknote images. However, image processing techniques can generally be employed to analyze printing patterns and identify variations in ink density or alignment. Techniques such as thresholding, edge detection, and texture analysis can be utilized to detect and quantify uneven printing in banknote images. These techniques can help distinguish genuine banknotes with uniform printing from counterfeit ones with irregular or inconsistent patterns [14].
- **Color variable holographic yarn:** The third security feature extracted is the color variable holographic yarn. Color variable holographic yarn is a security feature in banknotes to prevent counterfeiting. This type of yarn exhibits color-changing properties when viewed from different angles. The holographic yarn is embedded in the banknote during the printing process, adding a layer of complexity to the design and making it difficult to replicate. The color variations in the holographic yarn can be detected and analyzed using image processing techniques to verify the banknote's authenticity. In detecting counterfeit Bangladesh banknotes, the color variable holographic yarn is one of the security features extracted from acquired banknote images and used in the classification process [15].

(a)

(b)

Figure 3(a) (b)**:** Front Side and Back Side of the Note

The Bangladesh currency note of denomination 100 BDT, with dimensions measuring 140×62mm, bears distinct security features to ensure its authenticity. Signed by Fazle Kabir, Governor of the Bangladesh Bank, this note is printed on highly durable paper embedded with synthetic fibers, enhancing its resilience against wear and tear.

Integral to its security measures, the note incorporates several watermarks, including a prominent portrait of Bangabandhu Sheikh Muzibur Rahman, revered as the Father of the Nation. A bright electrotype watermark displaying the numerical '100' is positioned just below the portrait, alongside the Bangladesh Bank's logo, accentuating the note's authenticity. Furthermore, the note features intricate designs in intaglio ink, discernible by their rough texture when rubbed by a finger. These include seven parallel diagonal straight lines, the portrait of Bangabandhu Sheikh Muzibur Rahman, and three small dots intended for tactile recognition by the visually impaired. Notably, the denomination '100' is printed with Optically Variable Ink (OVI), exhibiting a color shift from golden to green upon oscillation of the note. A 4mm security thread, embedded on the left side, bears the Bangladesh Bank's logo and the text '100 uàNà', alternating between white and black depending on the viewing angle. Latent printing of the denomination '100' is revealed when the note is held horizontally, further bolstering its security features.

Additionally, repeated microprints of the text 'BANGLADESH BANK' adorn the note's surface, visible along the security thread and adjacent to the denomination '100'. These microprints, along with the portrait of Bangabandhu Sheikh Muzibur Rahman and the National Monument, serve as additional security against counterfeiting. On the reverse side, microprints of 'BANGLADESH BANK' are repeated above the denomination '100', complemented by the intricate depiction of Tara Mosque in intaglio ink. These features, discernible only under magnification, underscore the note's authenticity and deter counterfeit replication. Collectively, these security measures contribute to the robustness of Bangladesh's currency and safeguard against fraudulent activities within its financial system.

B. Image Processing Techniques

The specific image processing techniques used in the paper for extracting security features from banknote images are not mentioned in the provided sources. However, image processing techniques are commonly employed in computer-aided detection systems for various applications, including feature extraction, noise reduction, and image enhancement. It can be inferred that similar image processing techniques may have been used in this paper for preprocessing the banknote images, enhancing the visibility of security features, and segmenting the regions of interest. The paper mentions that the captured banknote images are in RGB color, which suggests that color-based image processing techniques may have been utilized. Additionally, the paper mentions that the captured images are heavy and have more noise, indicating that noise reduction techniques may have been applied.

a) Image preprocessing

To extract features effectively, images of the currency are collected with suitable resolutions for both abstraction and brightness. Abstraction resolution refers to the number of pixels or dots per inch of a digital image. In contrast, brightness resolution concerns the accuracy with which pixel brightness represents the intensity of the original image. Data preprocessing operations are typically applied to prepare the currency images for feature extraction. These operations ensure the images are formatted appropriately, optimizing them for subsequent feature extraction. Upon input into the system, each picture undergoes resizing to a standardized size of (250 * 120) pixels. Subsequently, the resized image is transformed into an array format.

Figure 4: Converting Image to an Array

Furthermore, to ensure compatibility with the model, the array is normalized. This normalization process adjusts the pixel values to fall within the range of 0 to 255. Normalizing the pixel values makes the input data standardized, facilitating more consistent and accurate processing by the model.

b) Image Segmentation

In the context of BDT 100, image segmentation (Fig.5) involves breaking down the digital image of a BDT 100 note into separate segments or regions. Each segment corresponds to a specific area or currency feature, such as the watermark, security thread, or denomination number. By segmenting the BDT 100 image, we can isolate and analyze these components individually, allowing for a more detailed examination and accurate detection of counterfeit elements.

Figure 5: Segmented Images

c) Edge Detection

Edge detection refers to a collection of mathematical techniques to identify points in a digital image with sharp changes in brightness or, formally, discontinuities. These points of sharp brightness change are typically organized into curved line segments known as edges. This concept is analogous to step detection in 1D signals and change detection over time. Edge detection is pivotal in image processing, machine vision, and computer vision, particularly feature detection and extraction. It is a fundamental tool for locating object boundaries within images by detecting brightness discontinuities. This technique is widely used in image segmentation and data extraction across various domains, including image processing, computer vision, and machine vision. The theory of edge detection, rooted in one-dimensional analysis, extends naturally to two dimensions with an accurate approximation for calculating derivatives. Image segmentation, a crucial aspect of edge detection, is employed to identify objects and boundaries, such as lines and curves within an image.

Techniques like Scale-Invariant Feature Transform (SIFT) keypoint detection are often utilized in preprocessing steps before feature recognition. SIFT keypoint detection aids in identifying significant points within the image pixels, which remain invariant across different scales. This technique facilitates the detection of counterfeit notes by identifying key points indicative of potential irregularities or anomalies. By leveraging SIFT key points, counterfeit note detection systems can swiftly identify suspicious features within images, contributing to efficient and accurate detection processes.

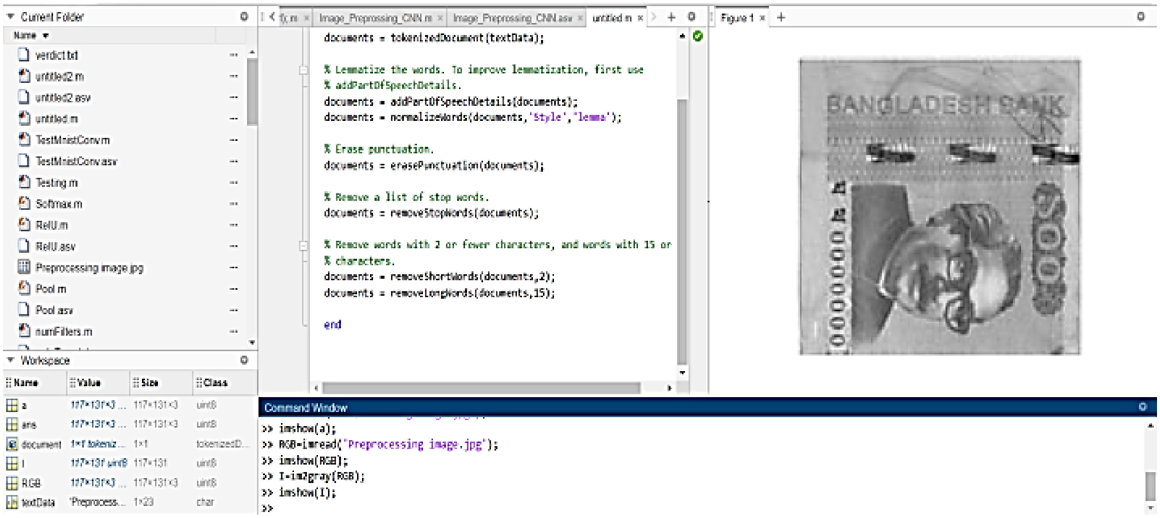

Figure 6: Grayscale conversation

While the gathered photographs of Bangladeshi currency are in RGB format, the notes provided for system testing are in color graphics. Therefore, converting these color images to grayscale becomes necessary. In grayscale images, each pixel has only one color value, unlike RGB images, where each pixel comprises three color channels. Specifically, grayscale photos consist of only two channels: black and white, simplifying the processing task and enabling more efficient analysis.

d) Edge Detection

Edge detection refers to a collection of mathematical techniques to identify points in a digital image with sharp changes in brightness or, formally, discontinuities. These points of sharp brightness change are typically organized into curved line segments known as edges. This concept is analogous to step detection in 1D signals and change detection over time. Edge detection is pivotal in image processing, machine vision, and computer vision, particularly feature detection and extraction. It is a fundamental tool for locating object boundaries within images by detecting brightness discontinuities. This technique is widely used in image segmentation and data extraction across various domains, including image processing, computer vision, and machine vision. The theory of edge detection, rooted in one-dimensional analysis, extends naturally to two dimensions with an accurate approximation for calculating derivatives. Image segmentation, a crucial aspect of edge detection, is employed to identify objects and boundaries, such as lines and curves within an image.

Techniques like Scale-Invariant Feature Transform (SIFT) key point detection are often utilized in preprocessing steps before feature recognition. SIFT essential point detection aids in identifying significant points within the image pixels, which remain invariant across different scales. This technique facilitates the detection of counterfeit notes by identifying key points indicative of potential irregularities or anomalies. By leveraging SIFT key points, counterfeit note detection systems can swiftly identify suspicious features within images, contributing to efficient and accurate detection processes.

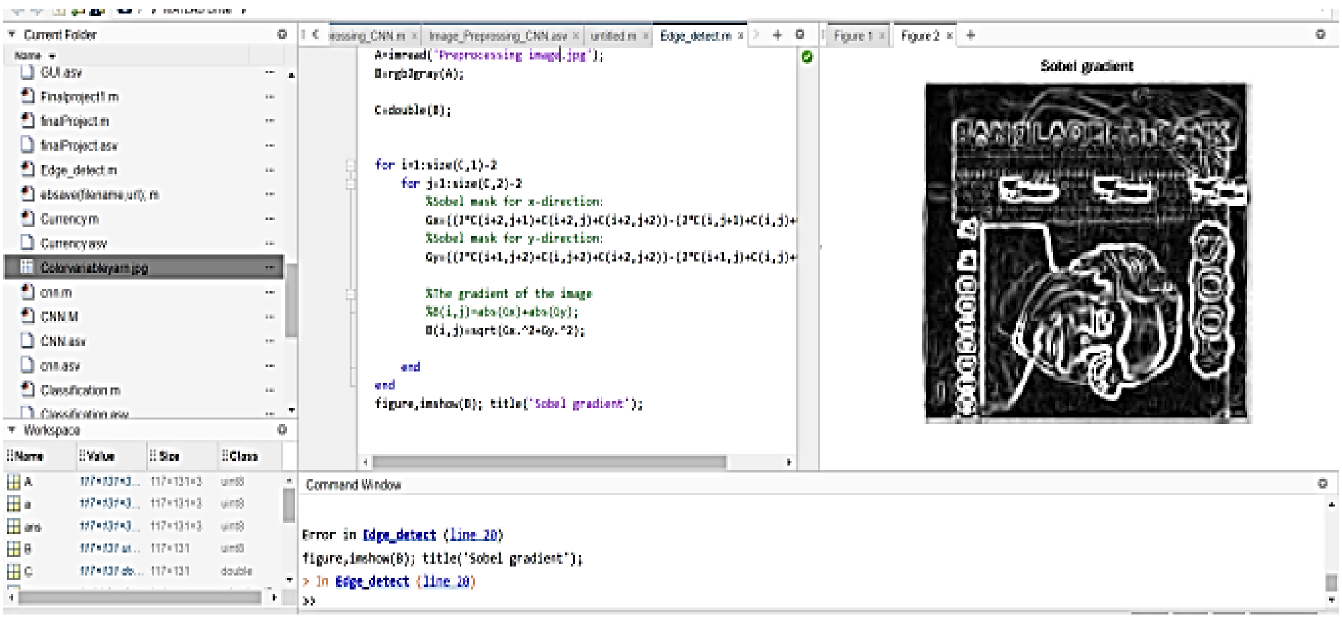

Figure 7: Edge detection

e) *Convolutional neural network using classification*

A Convolutional Neural Network (CNN) utilizing classification is a powerful tool for identifying and distinguishing between different classes of objects or images, including currency denominations such as the BDT 100 note.

In the context of BDT 100 note classification using CNN, the network is trained on a dataset comprising genuine BDT 100 notes and images of counterfeit notes or other denominations. During training, the CNN learns to extract relevant features from the input images and assign probabilities to each class, indicating the likelihood that the input image belongs to a particular class (e.g., genuine BDT 100 note, counterfeit note, or other denominations).

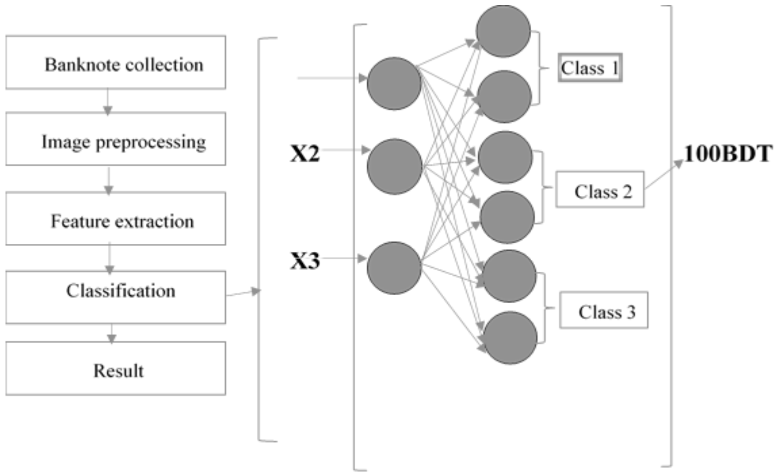

Figure 8**:** Convolutional neural network using classification

The CNN typically consists of convolutional, pooling, and fully connected layers. The convolutional layers apply filters to the input images, capturing local patterns and features. The pooling layers downsample the feature maps obtained from the convolutional layers, reducing the spatial dimensions while retaining essential features. Finally, the fully connected layers process the extracted features and make predictions about the class of the input image.

Once trained, the CNN can effectively classify new images of BDT 100 notes by analyzing their features and comparing them to the learned patterns from the training data. This classification process enables the system to automatically identify and flag potential counterfeit BDT 100 notes, thereby contributing to fraud detection and prevention efforts in the financial sector. Additionally, CNNs offer scalability and adaptability, allowing for the integration of advanced features and enhancements to improve classification accuracy over time.

IV. RESULTS AND DISCUSSIONS

The initial training phase involved the entire training dataset, utilizing a uniform learning rate of 0.001 across all layers. Initially, 350 images were employed to train the network for 250 cycles. Subsequently, the network underwent re-training for an additional 400 cycles, increasing the training accuracy score from 85.4% to 90.03%.

Table 1 below summarizes the outcomes generated by the model. The model achieved a % success rate of 82% in distinguishing between original and fake Bangladeshi currency 100Tk note. However, it encountered difficulties in two cases where it failed to recognize original currency notes with more stains. Enhancing the dataset size by incorporating more captured images is recommended to improve the success rate.

Table 1. Prediction Accuracy Values for Differentiating between Fake and Original Currency Notes

S. No.	Training Set	Validation Set	Cycles	Epoch	Training Accuracy (%)	Input Image	Probability of Fake	Probability of Original	Outcome
1	300	50	400	42	90.03	500_testing.jpg (Original)	0.558	0.451	Fail
2	300	50	400	42	90.03	1006.jpg (Original)	0.001	0.989	Success
3	300	50	400	42	90.03	1004.jpg (Fake)	0.845	0.185	Success
4	300	50	250	28	85.4	500_testing.jpg (Original)	0.423	0.577	Fail

5	300	50	250	28	85.4	1006.jpg (Original)	0.005	0.995	Success
6	300	50	250	28	85.4	1004.jpg (Fake)	0.760	0.255	Success

The currency forensics system was prototyped using the MATLAB environment on a specific platform. In a subsequent experiment, multiple networks were trained, each utilizing a feature vector with one characteristic excluded. This approach aimed to assess the accuracy level when individual characteristics were omitted, thus identifying the effectiveness of each characteristic in contributing to the system's performance.

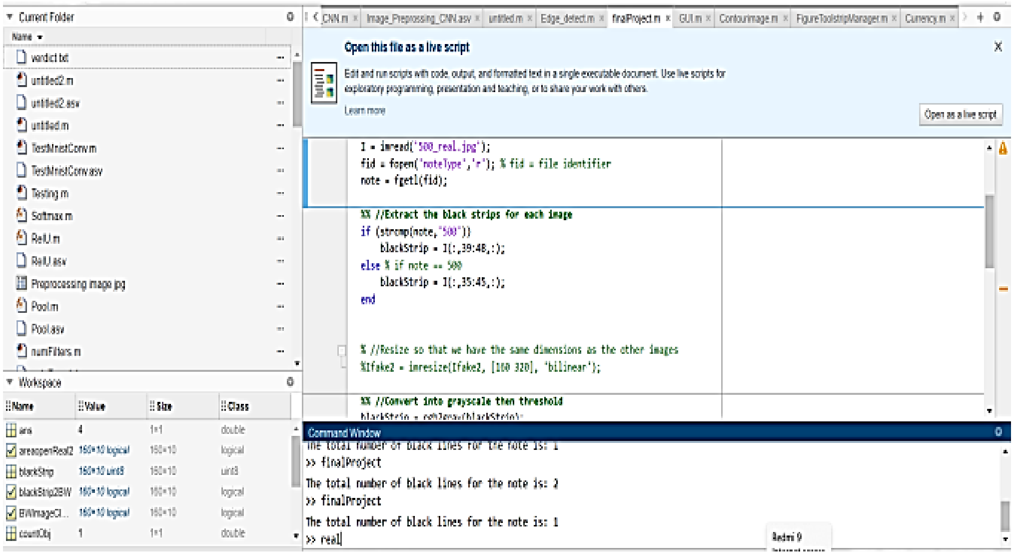

Figure 9: Output (Real)

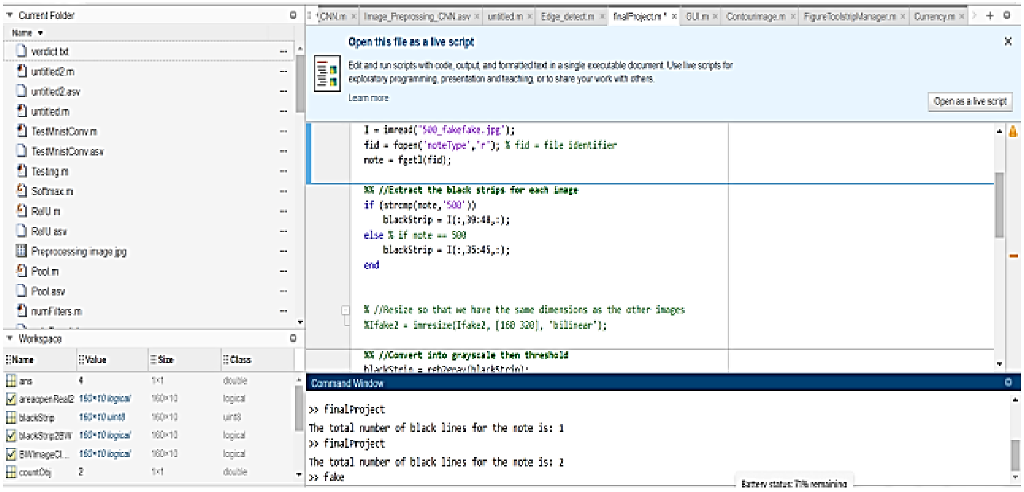

Figure 10: Output (Fake)

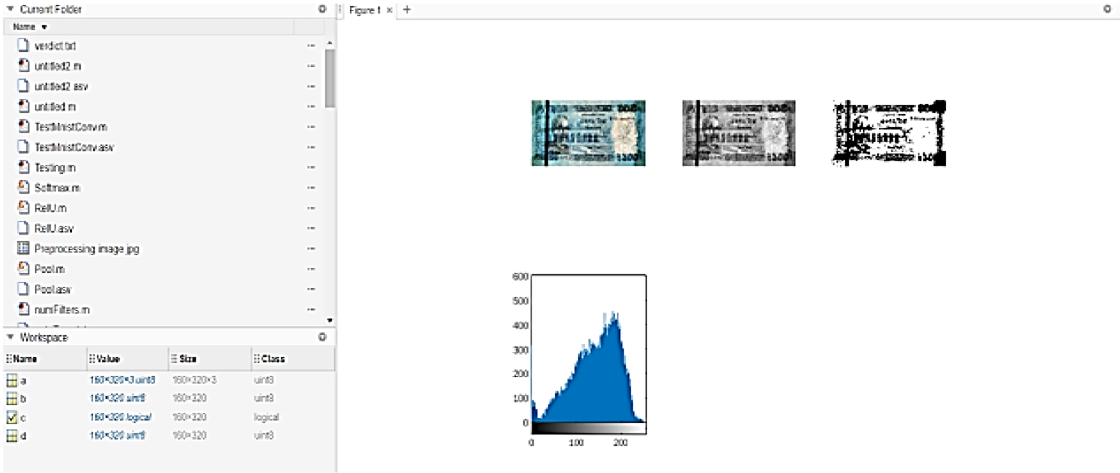

Figure 11: Output (Real Histogram)

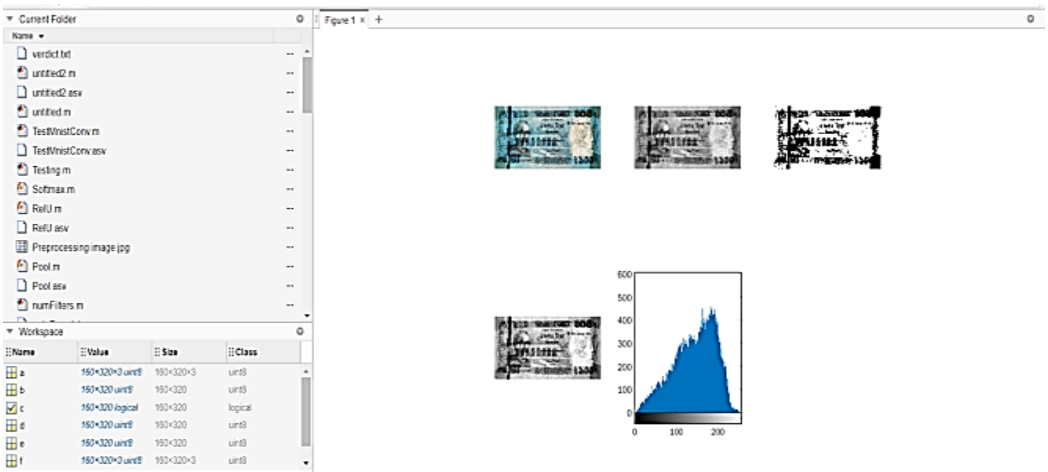

Figure 12: Output (Fake Histogram)

The results of the proposed algorithm where we applied all the above techniques and obtained optimized results. The run time was not increased much, mainly while the accuracy was raised to 95.86%.

Accuracy Rate = (No. of Correct readings / Total No. of readings) *100

= (27/30) *100

= 90.03%

Average time for code to run=6.1895 seconds.

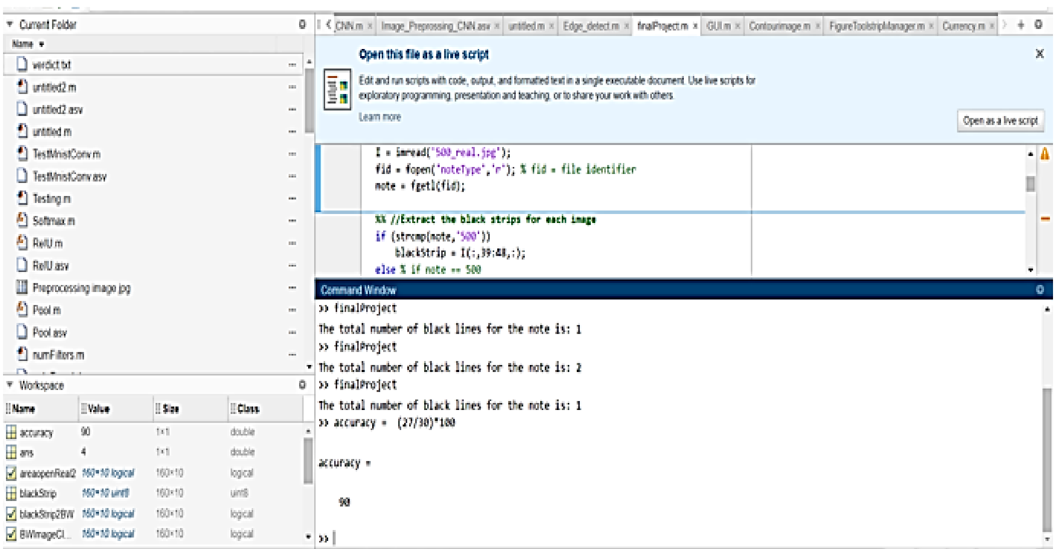

Figure 13: Accuracy Rate

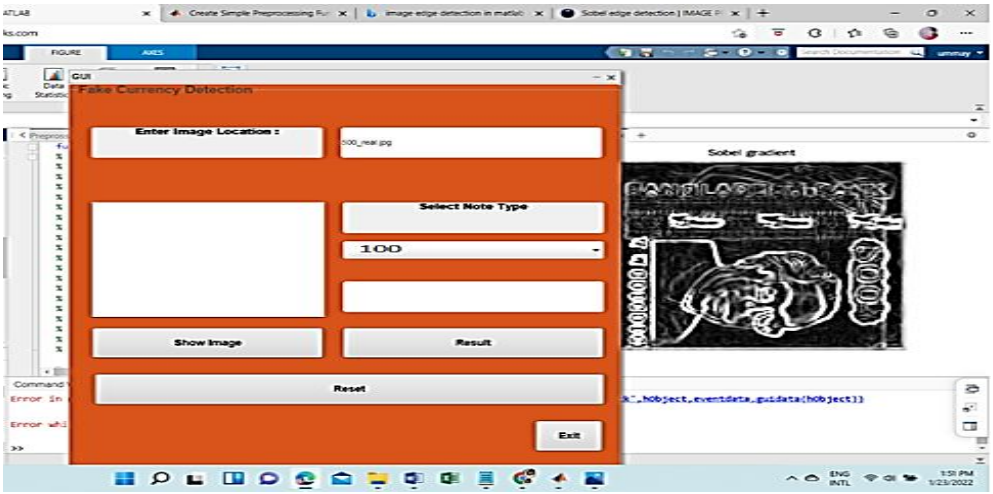

Figure 14: Fake Currency Detection Interface

In Fig.9, the output depicts a genuine banknote, while Fig.10 showcases the output corresponding to a counterfeit banknote. Furthermore, Fig.11 and Fig.12 illustrate the histograms of authentic and counterfeit banknotes, respectively. Fig.13 displays the accuracy rate of the detection system, providing insights into its performance. Lastly, Fig.14 visually represents the process of fake currency detection.

Phase two of the project encountered limitations: counterfeit currency detection image preprocessing and developing a cloud-based Android application to complement phase one. These limitations include:

Internet Connectivity and Speed: The Android application relies on internet connectivity with sufficient upload and download speeds to obtain prompt results.

Lighting Constraints for Counterfeit Detection: Optimal conditions for the algorithm to function effectively require the Region of Interest (RoI) image on the currency note to be captured under relatively dim lighting conditions. This ensures that the UV light illuminated is distinguishable.

A. Real-World Application and Limitations

CNNs can be trained to analyze images of Bangladesh currency notes, focusing on security features such as watermarks, security threads, and intricate designs. Automated systems based on CNNs can efficiently scan large volumes of banknotes, accurately identifying counterfeit ones. This application can assist banks, currency exchange centers, and businesses detect fake currency circulating in the market. Integrating CNN-based counterfeit detection algorithms into retail point-of-sale systems can help prevent counterfeit currency from entering circulation. When customers make transactions using Bangladesh currency, the system can quickly verify the authenticity of banknotes based on their visual features. This real-time authentication capability enhances security and trust in retail transactions. The central bank of Bangladesh can utilize CNN-based counterfeit detection technologies to monitor the prevalence of counterfeit currency in circulation and assess the effectiveness of anti-counterfeiting measures. By analyzing data collected from various sources, including banks, financial institutions, and law enforcement agencies, the central bank can gain insights into emerging counterfeit trends and implement targeted interventions to safeguard the integrity of the national currency. CNN-based counterfeit detection systems can be deployed at border checkpoints and customs facilities to combat currency smuggling and illegal cross-border transactions. By inspecting incoming and outgoing currency, these systems can identify counterfeit Bangladesh currency notes concealed in luggage, shipments, or cash transfers, strengthening border security measures and preventing financial crimes.

One of the primary challenges is the availability of labeled data for training CNN models tailored explicitly to Bangladesh currency. Obtaining a diverse and representative dataset of authentic and counterfeit banknotes can be challenging, hindering the development and generalization of CNN-based detection systems. Counterfeiters continually innovate new techniques to produce counterfeit currency that mimics genuine notes. CNN models trained on a specific set of counterfeit features may struggle to detect variations or novel counterfeit methods not represented in the training data, leading to false negatives and reduced detection accuracy. Integrating CNN-based counterfeit detection systems into existing infrastructure, such as banking systems, ATMs, or border security checkpoints, requires careful consideration of technical, regulatory, and operational requirements. Deployment challenges include system compatibility, real-time performance, and maintenance of detection accuracy over time.

Counterfeit detection systems often collect and analyze visual data, including images of individuals, their transactions, or personal belongings. Ensuring the privacy and security of this data is essential to prevent unauthorized access, misuse, or surveillance, particularly in contexts such as retail transactions or border security checks. False positives—incorrectly identifying genuine items as counterfeit—can have significant negative consequences for individuals and businesses, including financial losses, reputational damage, and legal implications. Ethical considerations involve minimizing the risk of false accusations and providing recourse mechanisms for affected parties to appeal decisions. Counterfeit detection systems can have broader social impacts, including implications for employment, economic disparities, and access to goods and services. Ethical considerations involve balancing the benefits of counterfeit detection, such as protecting consumers and businesses, with potentially damaging consequences, such as job displacement in counterfeit production industries or increased barriers to access for marginalized communities. Ethical counterfeit detection practices should adhere to relevant laws, regulations, and industry standards governing data privacy, consumer protection, intellectual property rights, and anti-discrimination. Compliance with regulatory requirements helps ensure that counterfeit detection systems operate within legal and ethical boundaries, protecting the rights and interests of all stakeholders involved.

V. CONCLUSION

In this study, the authors have proposed an image-based methodology for identifying counterfeit Bangladesh banknotes of 100 BDT. Utilizing a CNN classifier, the authors extracted three crucial security features – watermark, uneven printing, and color variable holographic yarn – from acquired images of the banknotes. Their approach considered two variations of the 100 BDT banknotes. Moreover, the authors plan to extend this methodology to the Android framework to enhance its portability, ensuring wider accessibility. The authors developed the system using MATLAB, incorporating a user-friendly interface for ease of use. Their primary motivation behind this endeavor was to create a system that is accessible and user-friendly, mainly catering to visually impaired individuals. By providing successful identification outcomes for the paper currencies currently circulating in Bangladesh, the authors aim to contribute to mitigating counterfeit currency-related issues in the region.

In conclusion, the image-based methodology coupled with CNN classification presented by the authors presents a promising solution for detecting counterfeit Bangladesh banknotes. The integration of this technique into the Android framework will further enhance its accessibility and usability, making it a valuable tool for both visually impaired individuals and the broader community. Through this work, the authors strive to bolster efforts to maintain the integrity of currency systems and safeguard against financial fraud.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest

REFERENCES

[1] "Counterfeit Detection using Deep Learning." International Journal of Advanced Research in Science, Communication and Technology, undefined (2023). doi: 10.48175/ijarsct-9436

[2] "Detection of Fake Currency using Machine Learning." International Journal For Science Technology And Engineering, undefined (2023). doi: 10.22214/ijraset.2023.51314

[3] Marjuk, Ahmed, Siddiki., Md., Naimul, Hossain., Khadija, Akhter., Md., Riazur, Rahman. "Bangladeshi Currency Identification and Fraudulence Detection Using Deep Learning and Feature Extraction." International journal of computer science and mobile computing, undefined (2023). doi: 10.47760/ijcsmc.2022.v12i01.001

[4] Homaira, Nowshin., Juel, Sikder., Utpol, Das. "A Deep Learning Approach for Detecting Bangladeshi Counterfeit Currency." undefined (2022). doi: 10.1007/978-3-031-19958-5_51

[5] Haider, Khalil, Easa., A., A., Saber., Noor, Kaylan, Hamid., Hindren, A., Saber. "Machine learning based approach for detection of fake banknotes using support vector machine." Indonesian Journal of Electrical Engineering and Computer Science, undefined (2023). doi: 10.11591/ijeecs.v31.i2.pp1016-1022

[6] Ali, Hasan, Md., Linkon., Md., Mahir, Labib., Faisal, Haque, Bappy., Soumik, Sarker., Marium-E-Jannat., Saiful, Islam. "Deep Learning Approach Combining Lightweight CNN Architecture with Transfer Learning: An Automatic Approach for the Detection and Recognition of Bangladeshi Banknotes." arXiv: Computer Vision and Pattern Recognition, undefined (2020).

[7] A., Chandu, Naik. "Deep Learning Approaches for Automated Detection of Fake Indian Banknotes." undefined (2023). doi: 10.1109/ICICACS57338.2023.10100265

[8] Mangesh, M., Ghonge., Tejas, Kachare., Manisha, Sinha., Siddharth, Kakade., Siddharth, Nigade., Sandeep, Shinde. "Real Time Fake Note Detection using Deep Convolutional Neural Network." undefined (2022). doi: 10.1109/ICCSEA54677.2022.9936084

[9] Junfang Guo, Yanyun Zhao and Anni Cai 2010 Proc IEEE Int. Conf Network Infrastructure and Digital Content 359-363.

[10] D. O'Loughlin, M. O'Halloran, B. M. Moloney, M. Glavin, E. Jones, and M. A. Elahi, "Microwave Breast Imaging: Clinical Advances and Remaining Challenges," IEEE Trans. Biomed. Eng., vol. 65, no. 11, pp. 2580–2590, 2018.

[11] R. Bremananth, B. Balaji, M. Sankari and A. Ch0itra," A new approach to coin recognition using neural pattern analysis," IEEE Indicon 2005 Conference, Chennai, India, 11- 13 Dec. 2005.

[12] Takeda F. and Omatu S., Onami S., Kadono T. and Terada K, "A Paper Currency Recognition Method by a Small Size Neural Network with Optimized Masks by GA", Proceedings of IEEE World Congress on Computational Intelligence, 1994, 42434-246.

[13] Sanjana, Manoj Diwakar, Anand Sharma, "An Automated recognition of Fake or Destroyed Indian currency notes in Machine vision", IJCSMS, Vol. 12, April 2012.

[14] Z. Ahmed, S. Yasmin, M. N. Islam, R. U. Ahmed, "Image processing based Feature extraction Of Bangladeshi banknotes," Proc. Software, Knowledge, Information Management and Applications (SKIMA), pp.1-8, 18-20 Dec. 2014.

[15] [Online] http://fake currency detection. GitHub