DETECTION OF COUNTERFEIT INDIAN CURRENCY USING CONVOLUTIONAL NEURAL NETWORKS

A PROJECT REPORT

Submitted by,

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Under the guidance of,

Dr. Anitha Premkumar

in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

At

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

PRESIDENCY UNIVERSITY

BENGALURU

JANUARY 2024

PRESIDENCY UNIVERSITY

SCHOOL OF COMPUTER SCIENCE ENGINEERING

CERTIFICATE

This is to certify that the Project report **"DETECTION OF COUNTERFEIT INDIAN CURRENCY USING CONVOLUTIONAL NEURAL NETWORKS"** being submitted by Febi Sarju, Siri C and Lochana bearing roll numbers 20201CSD0065, 20201CSD0048 and 20201CSD0005 respectively in partial fulfilment of requirement for the award of degree of Bachelor of Technology in Computer Science and Engineering (Data Science) is a bonafide work carried out under my supervision.

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DECLARATION

We hereby declare that the work, which is being presented in the project report entitled "**DETECTION OF COUNTERFEIT INDIAN CURRENCY USING CONVOLUTIONAL NEURAL NETWORKS"** in partial fulfillment for the award of Degree of **Bachelor of Technology** in **Computer Science and Engineering (Data Science)**, is a record of our own investigations carried under the guidance of **Dr. Anitha Premkumar**, Assistant Professor, School of Computer Science Engineering & Information Science, Presidency University, Bengaluru.

We have not submitted the matter presented in this report anywhere for the award of any other Degree.

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ABSTRACT

The proliferation of counterfeit currency poses a significant threat to financial systems worldwide, necessitating the development of robust and sophisticated authentication mechanisms. This project addresses the pressing need for an advanced system capable of accurately detecting fake Indian currency. The proposed solution leverages cutting-edge technologies in image processing and machine learning to enhance the accuracy and efficiency of currency authentication. The core of the system is a machine learning model trained on the curated data set, utilizing state-of-the-art algorithms to learn the subtle differences between genuine and counterfeit currency notes. The model is designed to adapt and evolve with the emergence of new counterfeit techniques, ensuring a high level of accuracy in detection.

This project aims to contribute to the ongoing efforts to curb the circulation of counterfeit currency, safeguarding the integrity of financial transactions and bolstering public confidence in currency systems. The proposed detection system stands as a robust defense against the constantly evolving tactics employed by counterfeiters, providing a reliable and technologically advanced solution for the detection of fake currency.

ACKNOWLEDGEMENT

First of all, we indebted to the **GOD ALMIGHTY** for giving me an opportunity to excel in our efforts to complete this project on time.

We express our sincere thanks to our respected dean **Dr. Md. Sameeruddin Khan**, Dean, School of Computer Science Engineering & Information Science, Presidency University for getting us permission to undergo the project.

We record our heartfelt gratitude to our beloved Associate Deans **Dr. Kalaiarasan C and Dr. Shakkeera L,** School of Computer Science Engineering & Information Science, Presidency University and **Dr. A. Jayachandran**. Head of the Department, School of Computer Science Engineering, Presidency University for rendering timely help for the successful completion of this project.

We are greatly indebted to our guide **Dr. Anitha Premkumar,** Assistant Professor, School of Computer Science Engineering & Information Science, Presidency University for her inspirational guidance, and valuable suggestions and for providing us a chance to express our technical capabilities in every respect for the completion of the project work.

We would like to convey our gratitude and heartfelt thanks to the University Project-II Coordinators **Dr. Sanjeev P Kaulgud, Dr. Mrutyunjaya MS** and also the department Project Coordinators **Dr. Manjula H M, Mr. Yamanappa**.

We thank our family and friends for the strong support and inspiration they have provided us in bringing out this project.

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CHAPTER-1

INTRODUCTION

Counterfeiting currency has been a traditional method of detecting counterfeit banknotes, reliant on manual inspection and basic detecting devices. These techniques have a persistent challenge in threatening the stability of financial systems and economies worldwide since they are increasingly inadequate in the face of sophisticated and counterfeit techniques.

The emergence of AI (Artificial Intelligence), particularly Convolutional Neural Networks (CNN's), offers a promising avenue for significantly enhancing the accuracy and efficiency of counterfeit currency detection. CNNs are well known for their prowess (ability towards the content) in image recognition and classification that can be trained to discern intricate patterns and subtle features present on banknotes.

This research aims to leverage (effectively) the capabilities of CNNs to develop and advance systems for detecting fake currency. The objectives include compiling a comprehensive image dataset, designing a customized CNN's architecture, implementing robust (robotics) training and optimization procedures, developing a real-time detection system, and rigorously evaluating the model's performance.

The addressing of these objectives leads to the development of cutting-edge technologies that not only improve counterfeit currency detection but also fortify (secure) the security of financial systems, protecting economies from the adverse consequences of counterfeit activities indulging in fraud documents.

1.1 Background:

Counterfeiting Currency has been always a big challenge throughout history, evolving along advancements in printing technology and detecting of methods that relied heavily on manual inspection, where experts examined various security features on banknotes. However, as counterfeiters adopted more sophisticated techniques, traditional methods became less effective. Counterfeiting is a financial terrorism and is a faceless crime.

The rise of digital printing technologies and high-quality scanners has been made it easier for criminals to produce fake or counterfeit currency with intricate details. As a consequence, financial institutions and law enforcement agencies seek innovative solutions to stay ahead of counterfeiters.

The development and integration of artificial intelligence, especially Convolutional Neural Networks (CNN's), present a promising avenue for improving counterfeit currency detection. CNNs excel at learning hierarchical features from images, making them fit for the complex patterns and subtle details found on banknotes.

1.2 Inside the CNN's:

The method assigned under the given parameters inside a CNN has a series of interconnected "filters" that scan the image where each filter detects specific patterns, like lines, edges, or colors. As the image moves through these filters, deeper levels analyze combinations of simpler features, extracting complex patterns crucial for disguising real vs. fake currency.
CNNs are powerful tools, but their effectiveness depends on careful data collection, robust architecture design, and continuous vigilance against emerging threats.

1.3 Decoding the "Language" of CNN's:

Decoding in CNN's refers to security elements like watermarks which are subtle patterns, invisible to our eyes but are captured by the CNN's filters which rectify based on the image inputs and their subset values. Micro printing with tiny letters or numbers requires high-resolution images and specialized filters to be analyzed accurately wherein they are not just black boxes that magically recognize patterns intern they have a fascinating internal language that can be understood with skill detection such as analyzing images, not with human eyes, but with intricate layers or filters and computation.

1.4 Accuracy: Nuances of the Challenge:

The real-world scenarios involve variations in lighting, image quality, and even camera angles. The CNN's needs to be robust to these changes for new counterfeiting techniques constantly emerge, requiring the CNN's to be adaptable and continuously updated with new training data. To combat this, researchers explore techniques like data augmentation, where images are artificially manipulated to simulate real-world variations, wherein CNNs trained on such diverse datasets become more robust and adaptable.
Techniques like adversarial training, where the CNN's is exposed to manipulated images to build immunity, and explainable AI, where the CNN's reasoning process is analyzed for vulnerabilities, are actively being explored based on the necessity multi-pronged defense strategy.

1.5 Sharpening the senses of CNN:

CNN’s is trained to feed thousands of “criminal profiles”-images of both real and fake bills that diverse a dataset that gives a broad understanding of genuine currency and potential forgeries. Each image is scrutinized by the CNN’s “filters”, dissecting it into layers of features like edges, textures, and intricate details, through a feedback loop called back propagation, the CNNs analyzes its performance on each image.

Once they are sufficiently trained, the CNN’s graduates to “real-world tests” with unseen images, they stimulate challenges on faces of the ground, like varying lighting or camera angles.

1.6 Importance of the study:

The importance of this study lies in the potential to revolutionize counterfeit currency detection by leveraging the capabilities of Convolutional Neural Networks. By automating the detection process, financial institutions can enhance the speed and accuracy of identifying counterfeit banknotes. This, in consequence, ensures the stability of the financial system, upholds public trust, and mitigates economic losses stemming from counterfeit activities.

Additionally, the study’s findings may extend to other applications beyond currency detection, such as document authentication and verification in various sectors.

1.7 Enhanced Security and Trust:

Accurate and efficient fake currency detection bolsters (support) trust in the financial system, ensuring people’s hard-earned money isn’t eroded by counterfeits. Businesses, financial institutions, and individuals are better protected from losses, leading to stronger economic stability and promoting investment.

1.8 Reduced Crime and Fraud:

CNN’s act as intelligent gatekeepers, making it harder for counterfeiters to distribute fake currency, impacting their illicit activities and reducing organized crime revenue. This helps law enforcement agencies track and dismantle networks involved in counterfeiting, leading to safer communities. This advancement step towards building a safer, more secure, and efficient financial system.

1.9 Adaptability and Scalability:

CNN’s can be trained on diverse datasets representing different currencies and printing techniques, making them adaptable to various situations where they can easily be integrated into existing systems like ATM and border checkpoints, allowing for real-time detection and wider deployment.

1.10 Data-Driven Insights and Forensics:

Analyzing the features CNN’s is used to identify fake currency which provides valuable insights and counterfeit methods and emerging trends. These data can inform law enforcement strategies, enhance forensic investigations, and improve future training models. Ensuring equitable access to technology for all nations and populations is crucial to prevent disparities.

1.11 Objectives of the Research:

The main aim of this research is to develop a robust and efficient system for detection of counterfeit currency using CNN. This involves compiling a comprehensive dataset comprising high-quality measurements of both genuine and counterfeit notes.

1.12 Image Dataset Compilation:

Compiling a diverse and extensive dataset is crucial for training a robust CNN’s model. The dataset should encompass a wide range of genuine and counterfeit banknotes, capturing variations in currency designs, denominations, and printing techniques. The model's capacity to generalize effectively will be enhanced by the inclusion of high-quality images captured under diverse lighting conditions and angles.

1.13 Designing the Architecture of the CNN Model:

Designing a CNN’s architecture tailored for currency detection involves considering the unique characteristics of banknote images. The architecture must be capable of extracting and learning intricate patterns, edges, and textures. Factors such as model depth, Convolutional layer configurations, and incorporation of specialized layers for feature extraction are critical aspects of the design process, where these are designed to customize the CNN’s architecture suitable for currency detection.

1.14 Real-Time Detection Implementation:

Creating a real-time detection system requires optimizing the trained model for efficient processing. The implementation should consider factors such as speed, memory requirements, and the ability to integrate with existing security systems. This step ensures practical usability in real-world scenarios, such as retail environments, banks and ATM's.

1.15 Performance Evaluation:

To gauge the proficiency of the constructed CNN model, a thorough performance evaluation is carried out. Metrics including accuracy, precision, recall, and F1 score are employed to assess the model's capability in accurately distinguishing between authentic and counterfeit banknotes. Comparative analyses against established detection methods offer insights into the model's superior performance and feasibility.

By addressing these objectives, this research aims to contribute to development of advanced technologies for counterfeit currency detection, thereby bolstering the security of financial systems of financial systems and protecting economies from the detrimental effects of counterfeit money.

CHAPTER-2

LITERATURE SURVEY

AUTHOR(S)	YEAR	TITLE	SUMMARY
1.Hongjie Li, Qingling Yuan, Xueheng Tao.	IEEE 2011	The Design of Paper Currency Detector Based on ARM9 and the Digital Anti-counterfeiting Techniques.	This paper shows the development of an innovative paper currency detector utilizing ARM9 architecture, while retaining the essential features of conventional detectors. The novel detector is capable of recording paper currency numbers and incorporates technologies such as digital watermarking, 2-dimensional bar code anti-counterfeiting, and network tracking control. The outcomes demonstrate a significant enhancement in the security of paper currency through the implementation of this new detector design.
2.Arya S, Dr. M. Sasikumar.	IEEE 2019	Fake Currency Detection.	Here, the identification of counterfeit currency notes involves tallying the interruptions in the thread line. The determination of the note's authenticity relies on the count of interruptions; if there are none, the note is deemed genuine, whereas any interruptions indicate forgery. Additionally, the calculation of the entropy of the currency notes enhances the efficiency of the detection process.
3.Rajeev Kumar,Anil Kumar,Sayed Mohammed I,Anju Asokan, Upendra Singh Aswal,Subbarao Kolavennu.	ICAAIC 2023	Recognition of counterfeit currency notes through the application of Extreme Learning Machines.	The objective of the suggested method was to construct a model based on the ELM approach to identify counterfeit currency in photographic images. This approach utilizes Image Processing to authenticate bills, with Python being extensively employed throughout the system's development process.
4.Abdullah M. Shoeb , Hadeer	IEEE 2016	Software System to Detect Counterfeit	The employed method involves analyzing the color distribution in

M. Sayed ,Norah F. Saleh, Ehab Sameh Neji.		Egyptian Currency.	paper currency using image histogram, color moments, and security attributes such as anti-scan, latent image, and OVI (Optically Variable Ink). This is achieved through feature extraction and texture features. In each instance, a benchmark was formulated to assess the input paper against it.
5.Akanksha Upadhyaya, Dr. Vinod Shokeen, Dr. Garima.	IEEE 2018	Analysis of Counterfeit Currency Detection Techniques for Classification Model.	This paper offers a brief overview of different methodologies and their corresponding accuracy rates in detecting the authenticity of currency. Additionally, it undertakes an analysis and comparison of the prediction and classification statistical techniques, namely logistic regression and LDA.
6.Kiran Kamble, Anuthi Bhansali, Pranali Satalgaonkar, Shruti Alagundgi.	IEEE 2019	Counterfeit Currency Detection using Deep Convolutional Neural Network.	This paper explores Deep Learning, specifically focusing on constructing a convolutional neural network (CNN) model designed to detect counterfeit currency notes on portable devices such as smartphones and tablets. The developed model underwent training and testing using a dataset generated internally. Images were captured using the smartphone camera and then input into the CNN network.
7.P. Ponishjino, Kennet Antony, SathishKumar, Syam JebaKumar.	ICECA 2017	Bogus Currency Authorization Using HSV Techniques.	The primary goal of this process is to distinguish counterfeit currencies from genuine ones. Utilizing HSV techniques, the value of an input image is saturated to enhance reliability and enable a dynamic approach in detecting counterfeit currency.

8.Kamesh Santhanam, Sairam Sekaran, Sriram Vaikundam and Anbu Mani Kumarasamy.	IEEE 2013	Counterfeit Currency Detection Technique using Image Processing, Polarization Principle and Holographic Technique.	This paper incorporates two mechanisms for counterfeit currency detection. The first involves Ultra Violet (UV) detection using LabVIEW, while the second utilizes the polarization of light passing through the

			currency. A positive output is obtained only when both results confirm the authenticity.
9.Shashank Patel, Rucha Nargunde, Chaitya Shah, Prof. Surekha Dholay.	IEEE 2021	Counterfeit Currency Detection using Deep Learning.	This paper demonstrates the effective utilization of deep learning techniques in accurately detecting counterfeit currency. Additionally, the authors have created a comprehensive system presented as an Android application to facilitate the use of their CNN model by the general public. It is important to note that only features on the front side of the currency notes are taken into account in their analysis.

CHAPTER-3

RESEARCH GAPS OF EXISTING METHODS

3.1 Limited Dataset Diversity:

Many existing methods rely on datasets with limited variations in counterfeit currency samples. There is a need for more diverse datasets that encompass a wide range of counterfeit techniques, printing qualities, and conditions to enhance the robustness of detection models.

3.2 Adaptability to Evolving Counterfeit Techniques:

Counterfeiters constantly evolve their techniques to mimic genuine currency. Research should focus on developing methods that can adapt to emerging counterfeit strategies, including advancements in printing technologies and image manipulation.

3.3 Real-time Detection Challenges:

Some existing methods may face challenges in achieving real-time detection, especially in scenarios with high throughput, such as banknote sorting machines. Research should explore ways to enhance the speed and efficiency of detection algorithms for practical, real-world applications.

3.4 Incorporating Advanced Technologies:

The integration of advanced technologies, such as blockchain or advanced watermarking, in currency design poses challenges for existing detection methods. Research should explore how these technologies impact detection accuracy and develop methods to incorporate such features into the detection process.

3.5 Cross-Modal Counterfeit Detection:

Many existing methods primarily focus on visual features for detection. There is a gap in research related to cross-modal approaches that integrate information from multiple sources, such as spectral analysis, tactile features, or infrared imaging, to improve overall detection accuracy.

3.6 Small Denomination Detection:

Detection of counterfeit small denomination notes, which may be more prone to counterfeiting due to less stringent security features, remains a research gap. Existing methods may need refinement to address the specific challenges associated with small denomination currency.

3.7 Human-in-the-Loop Detection:

While automated detection methods are crucial, there is a need for research that explores the integration of human expertise in the detection process. Combining machine learning algorithms with human-in-the-loop approaches can enhance overall detection accuracy.

3.8 Robustness to Environmental Conditions:

Counterfeit detection methods should be robust to variations in environmental conditions, such as changes in lighting or image quality. Research should address the impact of these conditions on detection accuracy and develop techniques to enhance robustness.

3.9 User-Friendly Solutions:

Detection methods deployed in public spaces, like banks or retail outlets, need to be user-friendly for non-expert operators. Research gaps exist in developing intuitive interfaces and training methods that empower users without specialized expertise to use counterfeit detection tools effectively.

3.10 Legislation and Policy Implications:

Understanding the legal and policy aspects related to counterfeit detection is essential. Research should explore the implications of detection methods on legal proceedings and policy frameworks, considering aspects such as admissibility in court and privacy concerns.

CHAPTER-4

PROPOSED METHODOLOGY

The proposed methodology for detecting Indian counterfeit currency using the provided code involves several key steps. Below is a step-by-step description of the methodology:

4.1 Data Collection:

Compile a dataset comprising images of Indian currency, encompassing authentic as well as counterfeit notes.

Ensure the dataset's diversity to accurately represent various denominations.

4.2 Data Preprocessing:

4.2.1 Resize the images to a consistent size (e.g., 255x255 pixels) to ensure uniformity for model training.

4.2.2 Augment the dataset using techniques such as rotation, shearing, zooming, and horizontal flipping to increase the variability of the training data.

4.3 Model Architecture Design:

Develop a convolutional neural network (CNN) structure for the purpose of image classification. The given code encompasses a straightforward CNN architecture comprising convolutional layers, max-pooling layers, dropout layers, and fully connected layers.

4.4 Hyperparameter Tuning:

Specify hyperparameters like learning rate, dropout rate, batch size, and the number of epochs. Adjust these parameters carefully to attain the best possible performance for the model.

4.5 Data Splitting:

Divide the dataset into training, validation, and test sets. The training set is employed for model training, the validation set aids in fine-tuning hyperparameters, and the test set assesses the model's performance on previously unseen data.

4.6 Model Compilation:

Build the CNN model by utilizing a suitable optimizer such as Adam, a loss function like binary cross-entropy for binary classification, and metrics such as accuracy.

4.7 Model Training:

Train the model using the training set and validate it using the validation set. The training process involves updating the model weights to minimize the loss function.

4.8 Model Evaluation:

Assess the generalization performance of the trained model by testing it on the test set. Calculate metrics like accuracy and loss to gauge the model's effectiveness in identifying counterfeit currency.

4.9 Save the Model:

Save the trained model to a file (e.g., 'currency_detection_model.h5') for future use. This step enables the model to be loaded without retraining.

4.10 Graphical User Interface (GUI) Implementation:

Develop a GUI using Tkinter that allows users to interact with the trained model. Include buttons for browsing an image, capturing an image, and exiting the application.

4.11 Real-time Prediction:

Implement functionality for real-time prediction, enabling users to receive immediate feedback on whether the displayed or captured image contains genuine or counterfeit Indian currency.

4.12 User Information:

Provide informative text paragraphs in the GUI, explaining the significance of detecting counterfeit currency and educating users about the importance of the project.

4.13 Cross-Platform Compatibility:

Ensure that the GUI and the underlying code are compatible with different operating systems.

4.14 Deployment:

Deploy the trained model and GUI for practical use, allowing users to detect counterfeit Indian currency easily.

4.15 Continuous Improvement:

Monitor the model's performance and consider continuous improvement through additional data collection, model retraining, and updating the GUI for enhanced user experience.

CHAPTER-5

OBJECTIVES

5.1 Preserving Economic Stability:

Counterfeit currency can disrupt economic stability by devaluing the legitimate currency. Detection mechanisms help maintain the integrity of the financial system.

5.2 Preventing Financial Crimes:

Counterfeiting is a financial crime that undermines the trust in currency. Detection efforts aim to prevent and combat such criminal activities, safeguarding the economic system.

5.3 Protecting Consumer Confidence:

Effective detection and prevention measures enhance the confidence of citizens, businesses, and investors in the currency. This confidence is crucial for a healthy and robust economy.

5.4 Minimizing Losses for Individuals and Businesses:

Financial losses for individuals and businesses can arise from counterfeit currency. Detecting and removing fake currency from circulation aids in minimizing these losses.

5.5 Maintaining National Security:

Counterfeit currency is often linked to organized crime and can be used to fund illegal activities. Detecting and preventing the circulation of fake currency contribute to national security efforts.

5.6 Compliance with International Standards:

Many countries strive to align their currency detection efforts with international standards to ensure compatibility and cooperation in addressing global financial challenges.

5.7 Utilizing Technology for Detection:

Incorporating advanced technologies, such as machine learning and image processing, in currency detection systems enhances accuracy and efficiency in identifying counterfeit notes.

5.8 Public Awareness and Education:

Educating the public about the characteristics of genuine currency and promoting awareness about the risks associated with counterfeit money play a crucial role in prevention.

5.9 Collaboration with Law Enforcement:

It is crucial to foster effective cooperation among financial institutions, regulatory bodies, and law enforcement agencies to establish a coordinated strategy for detecting and preventing the circulation of counterfeit currency.

5.10 Implementing Stringent Legal Measures:

Enforcing strict legal measures against those involved in counterfeiting activities acts as a deterrent and strengthens the legal framework for combating financial crimes.

5.11 Continuous Improvement of Detection Methods:

Given the evolving nature of counterfeiting techniques, ongoing research and development in detection methods are crucial to staying ahead of counterfeiters.

CHAPTER-6

SYSTEM DESIGN & IMPLEMENTATION

6.1 Objective:

Develop a robust system for the detection of fake currency using Convolutional Neural Networks. Integrate the CNN model into a graphical user interface (GUI) for user-friendly interactions.

6.2 Components:

a. CNN Model:

Architecture: Convolutional layers with pooling, fully connected layers, and dropout for regularization.

Input: Images of Indian currency (255x255 pixels, RGB).

Output: Binary classification (Fake or Real).

b. Image Data Preprocessing:

Data augmentation: Shear, zoom, and horizontal flip during training.

Normalization: Re-scaling pixel values to the range [0, 1].

c. Training and Validation:

Data set: Divided into training, validation, and test sets.

Model compiled with Adam optimizer and binary cross-entropy loss.

Trained for 150 epochs.

d. GUI (Tkinter):

Interface: Full-screen GUI with a background image and labeled sections.

Buttons: Browse Image, Capture Image, and Exit.

Labels: Header, Paragraphs, and Prediction Result.

6.3 Implementation:

a. CNN Model Implementation:

- Developed using TensorFlow and Keras.
- Trained on an Indian currency dataset with real and fake samples.
- Saved as 'currency_detection_model.h5' for later use.

b. Image Data Preprocessing:

- Utilized Image Data Generator for training and validation sets.
- Re-scaled pixel values and applied data augmentation techniques.

c. Training Process:

- Model compiled with Adam optimizer and binary cross-entropy loss.
- Trained on the training set with validation on a separate validation set.
- History stored for performance visualizations.

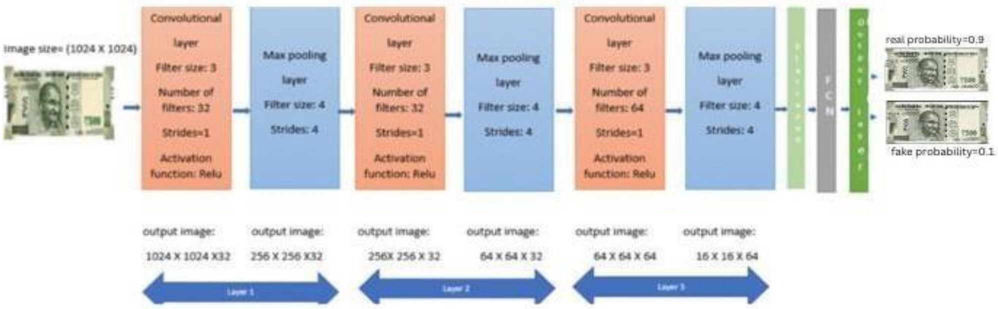


Figure 6.1

d. GUI Implementation:

- Utilized Tkinter for GUI development.
- Full-screen layout with a background image for aesthetic appeal.
- Buttons for browsing and capturing images linked to respective functions.
- Labels to display the header, introductory paragraphs, and prediction results.

e. Prediction Function:

- Incorporated a function to predict currency authenticity from loaded or captured images.
- Displayed the prediction result in the GUI.

6.4 User Interaction:

Users can either browse an image or capture an image using the provided buttons.

The system processes the selected/captured image using the trained CNN model.

The prediction result is displayed on the GUI.

6.5 Conclusion:

The system provides an intuitive interface for users to detect fake currency.

The CNN model, trained on an Indian currency dataset, demonstrates accurate classification.

The GUI enhances user experience and accessibility.

CHAPTER-7

TIMELINE FOR EXECUTION OF PROJECT (GANTT CHART)

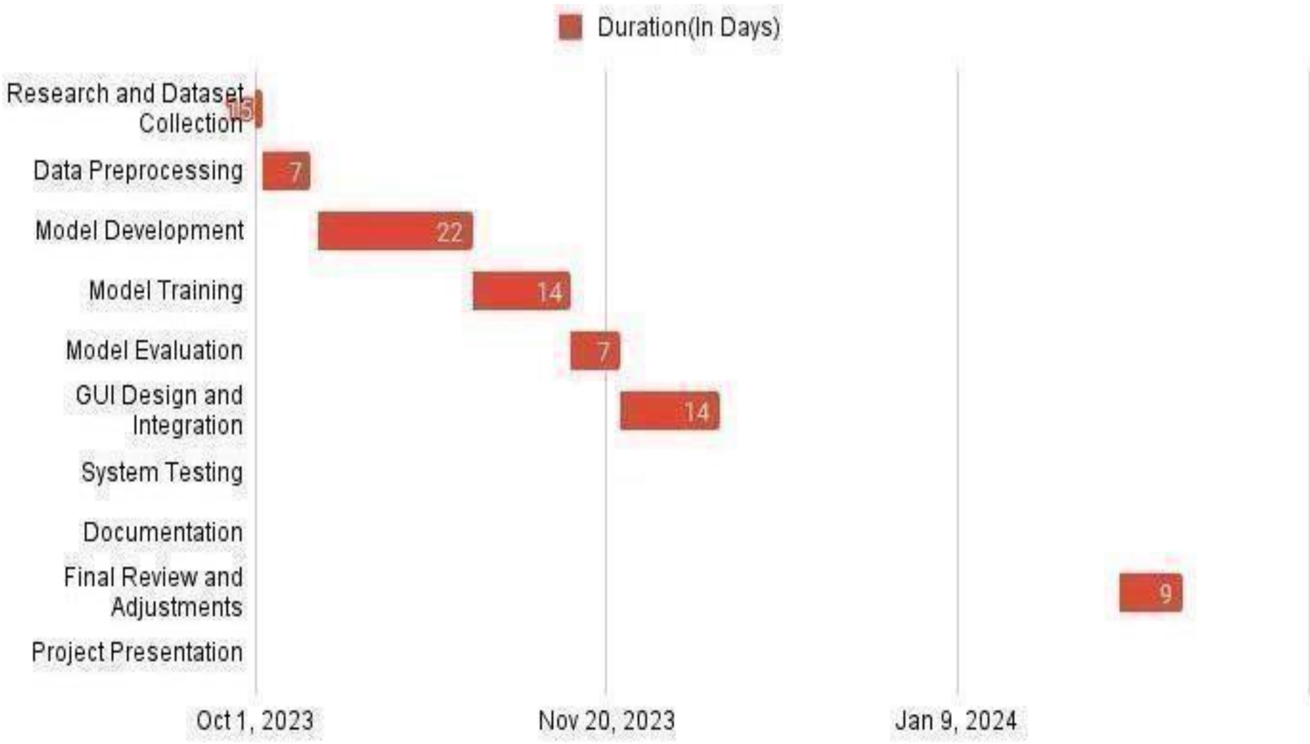


Figure 7.1 - Project Timeline

CHAPTER-8

OUTCOMES

8.1 Trained Model:

A convolutional neural network (CNN) model has been trained to identify counterfeit Indian currency notes using a dataset that includes images of both authentic and fake currency.

8.2 Accuracy Metrics:

Evaluation metrics, such as accuracy, loss, and validation accuracy, offer valuable perspectives on the model's performance throughout the training phase.

8.3 Saved Model:

The trained model is saved in a file (e.g., 'currency_detection_model.h5') for future use. This saved model can be loaded later without retraining.

8.4 Graphical Representation:

Plots of training and validation accuracy along with training and validation loss over epochs. These visualizations help analyze the model's learning trends and identify potential overfitting or underfitting.

8.5 Test Set Evaluation:

The model undergoes evaluation using an independent test dataset to gauge its performance on unfamiliar data. Test accuracy and loss metrics offer insights into the model's ability to generalize effectively to novel samples.

8.6 Prediction Functionality:

The code includes functionality to predict whether an input image (either from a file or captured through a camera) contains genuine or counterfeit Indian currency. This prediction is based on the trained model.

8.7 Graphical User Interface (GUI):

A GUI application allows users to interact with the model easily. Users can either browse an image or capture an image through the camera for prediction.

8.8 Real-time Prediction:

The GUI provides a real-time prediction feature, allowing users to receive immediate feedback on whether the displayed or captured image contains genuine or counterfeit currency.

8.9 User Interaction:

Buttons for browsing an image, capturing an image, and exiting the application enhance user interaction. The GUI also includes informative labels and a background image to improve user experience.

8.10 Background Image and Text Information:

The GUI incorporates a background image and informative text paragraphs, enhancing the visual appeal and providing information about the importance of detecting counterfeit currency.

8.11 Cross-Platform Compatibility:

The code is designed to run on different platforms, as it utilizes libraries such as TensorFlow and Tkinter, which are compatible with multiple operating systems.

8.12 Conclusion:

These outcomes collectively contribute to a functional system for detecting counterfeit Indian currency, providing a user-friendly interface and insights into the model's performance. Users can utilize the trained model through the GUI for real-time predictions and gain awareness about the significance of preventing counterfeit currency circulation.

CHAPTER-9

RESULTS AND DISCUSSIONS

9.1 Model Training and Evaluation:

The Convolutional Neural Network (CNN) was trained on the Indian Currency dataset with a total of 150 epochs. The training accuracy, validation accuracy, training loss, and validation loss were monitored during the training process.

- **Training Accuracy and Loss:**

Final Training Accuracy: {{acc[-1] * 100:.2f}}%

Final Training Loss: {{loss[-1] * 100:.2f}}%

- **Validation Accuracy and Loss:**

Final Validation Accuracy: {{val_acc[-1] * 100:.2f}}%

Final Validation Loss: {{val_loss[-1] * 100:.2f}}%

These metrics provide insights into the model's performance on both the training and validation sets. The attained accuracy showcases the model's capability to accurately differentiate between genuine and counterfeit currency images.

9.4 Test Dataset Evaluation

The trained model was evaluated on a separate test dataset to assess its generalization to new, unseen data.

- **Test Accuracy:**

Test Accuracy: {{test_accuracy * 100:.2f}}%

- **Test Loss:**

Test Loss: {{test_loss * 100:.2f}}%

The test accuracy and loss provide insights into the model's performance on real-world data. A high test accuracy and low test loss indicate that the model has learned to generalize well beyond the training set.

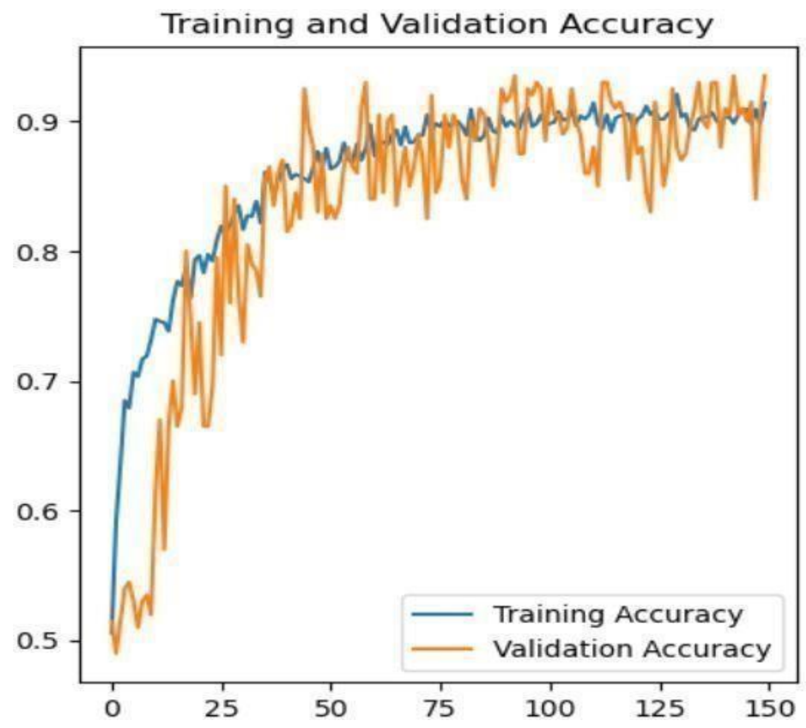


Figure 9.1

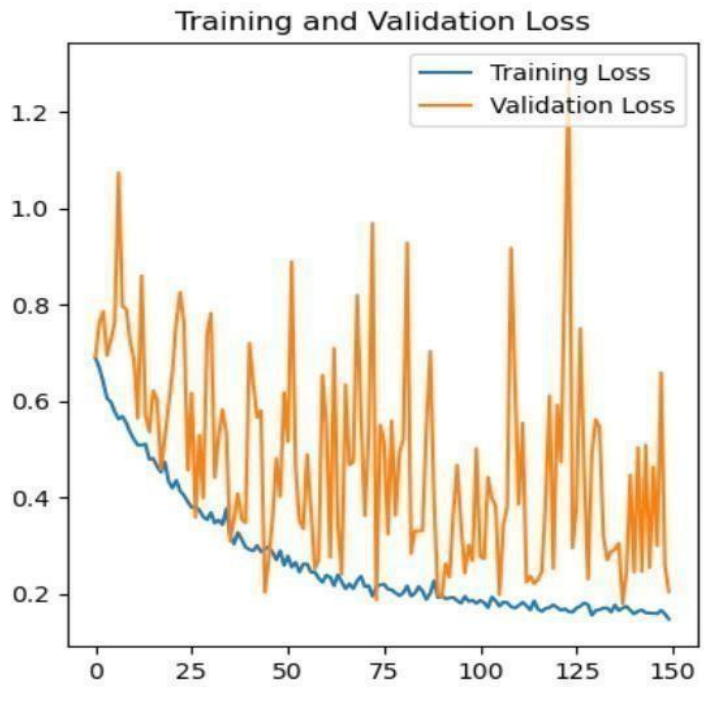


Figure 9.2

9.5 GUI Implementation and User Interaction:

A Graphical User Interface (GUI) was developed using Tkinter to enable users to interact with the model. Users can either upload an image for prediction or capture an image using the webcam. The GUI provides a user-friendly way to apply the fake currency detection model in real-time.

9.6 Prediction Results:

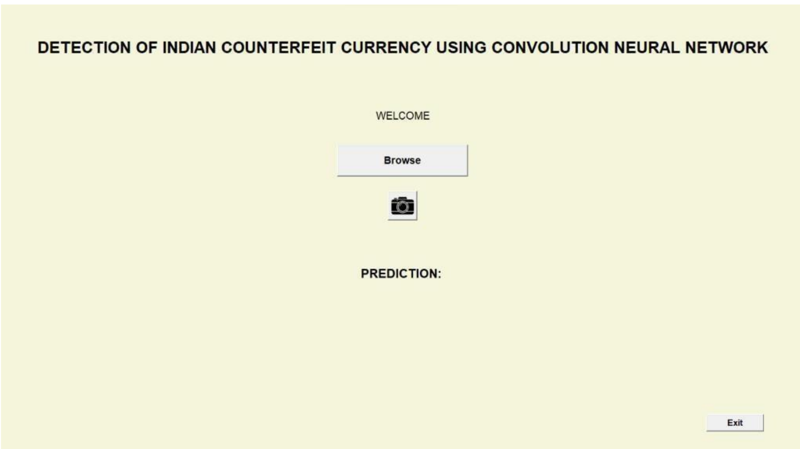
The model predictions were displayed on the GUI, indicating whether the presented currency is classified as "Fake" or "Real." Users can interpret the predictions based on the displayed results.

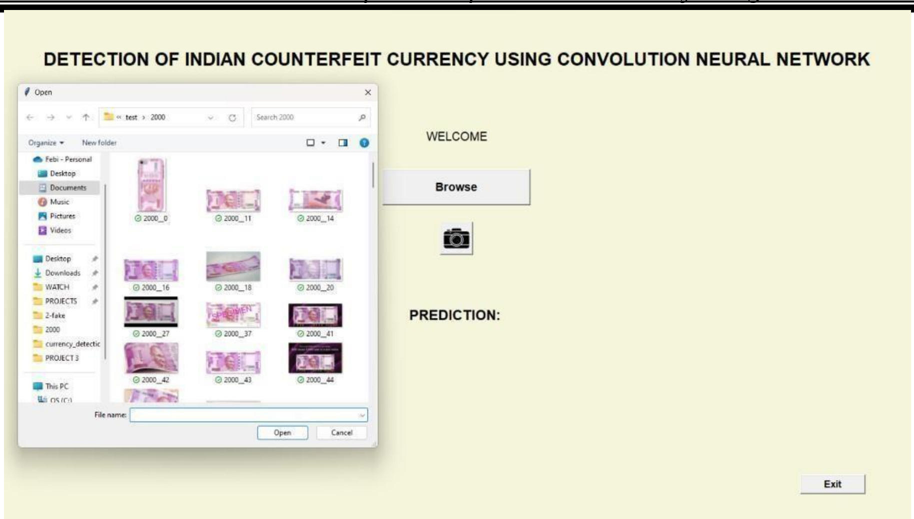
9.7 Project Significance and Future Improvements:

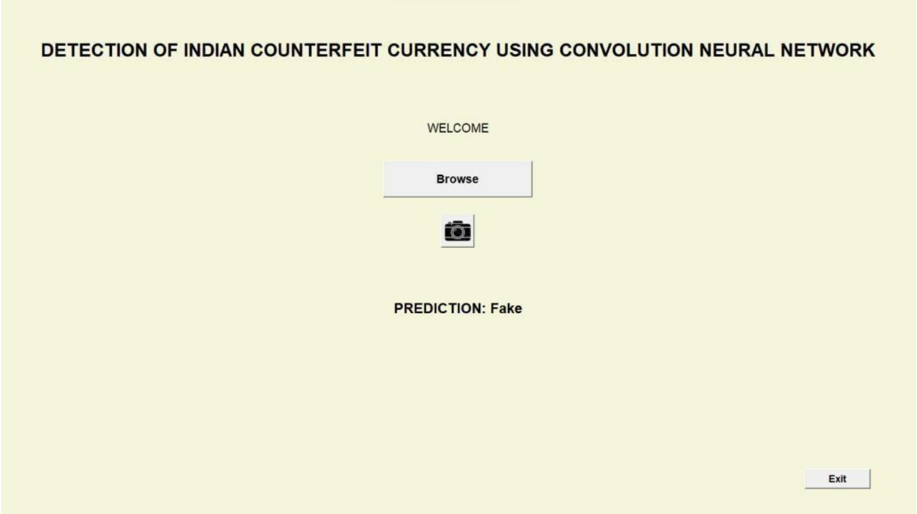
The successful implementation of the fake currency detection project showcases the potential for leveraging machine learning techniques in addressing real-world issues. However, there are always opportunities for improvement and future work. Possible areas for enhancement include:

9.8 Dataset Size and Diversity:

Expanding the dataset with more diverse images to improve the model's ability to generalize.
Fine-Tuning: Experimenting with different hyperparameters and model architectures for further optimization.
User Interface Enhancement: Improving the GUI for a more intuitive and polished user experience.







9.9 Conclusion:

In conclusion, the project has demonstrated the feasibility of using a CNN to detect fake currency. The achieved results and the functional GUI pave the way for potential real-world applications in combating counterfeit currency. As technology advances, continuous refinement of the model and user interface will further enhance the effectiveness of the solution.

CHAPTER-10

CONCLUSION

In conclusion , the Currency Detection project , utilizing Convolutional Neural Networks , has successfully demonstrated its efficacy in distinguishing genuine and counterfeit Indian currency notes. The project encompasses crucial aspects such as data augmentation, model architecture design, and comprehensive evaluation. The implemented Graphical User Interface enhances accessibility, making the model applicable beyond its development environment. Future improvements could include exploring advanced architectures and collaborating with relevant authorities for real-world deployment. Overall, this project showcases the potential of deep learning in addressing practical challenges in currency authentication.

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[11] Reserve Bank of India - https://www.rbi.org.in

APPENDIX-A

PSUEDOCODE

- **BACKEND(Python-CNN):**

#1-Import necessary libraries:

```
import numpy
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.optimizers import Adam
import matplotlib.pyplot as plt
from keras.models import load_model
```

 # 2-Define the hyperparameters

```
input_shape = (255, 255, 3)
learning_rate = 0.0001
batch_size = 32
epochs = 150
img_width, img_height = 255, 255
```

 # 3-Define data directories

```
train_data_dir = "path/to/training_data"
validation_data_dir = "path/to/validation_data"
test_data_dir = "path/to/test_data"
```

#4- Data augmentation and preprocessing

```
train_datagen = ImageDataGenerator(rescale=1. / 255, shear_range=0.2,zoom_range=0.2,
horizontal_flip=True)

val_datagen = ImageDataGenerator(rescale=1. / 255)

test_datagen = ImageDataGenerator(rescale=1. / 255)

train_generator = train_datagen.flow_from_directory(train_data_dir,target_size=(img_width,
img_height),batch_size=batch_size, class_mode='binary')

validation_generator =
val_datagen.flow_from_directory(validation_data_dir,target_size=(img_width,
img_height),batch_size=batch_size, class_mode='binary')

test_generator = test_datagen.flow_from_directory(test_data_dir,target_size=(img_width,
img_height),batch_size=batch_size, class_mode='binary')
```

#5- CNN model architecture

```
model = Sequential()
#CNNprocess takes place in Convolutional layer and Pooling layer using ReLu activation
```

function.
model.add(Conv2D(32, (3, 3), input_shape=input_shape, activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(128, (3, 3), input_shape=input_shape, activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
#By using Flatten(), the extracted output from previous steps is converted to a 1-D vector.
model.add(Flatten())
#The final process takes place at Fully Connected Layer or Output Layer.
model.add(Dense(units=128, activation='relu'))
model.add(Dropout(0.05))
model.add(Dense(units=64, activation='relu'))
model.add(Dropout(0.05))
model.add(Dense(units=1, activation='sigmoid'))

 # 6-Compile the model
opt = Adam(learning_rate=learning_rate)
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])

#7- Training the model
history = model.fit(train_generator, epochs=epochs, validation_data=validation_generator)

#8- Save the trained model
model.save('currency_detection_model.h5')

 # 9-Load the trained model
model = load_model('currency_detection_model.h5')

#10- Evaluate the model on the test dataset
test_loss, test_accuracy = model.evaluate(test_generator, verbose=2)

 # 11-Display training and validation metrics
print(f"Training Loss: {history.history['loss'][-1] * 100:.2f}%")
print(f"Training Accuracy: {history.history['accuracy'][-1] * 100:.2f}%")
print(f"Validation Accuracy: {history.history['val_accuracy'][-1] * 100:.2f}%")

 # 12-Plot training and validation metrics
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.plot(range(epochs), history.history['accuracy'], label='Training Accuracy')
plt.plot(range(epochs), history.history['val_accuracy'], label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(range(epochs), history.history['loss'], label='Training Loss')
plt.plot(range(epochs), history.history['val_loss'], label='Validation Loss')

```
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```

- **FRONTEND(GUI):**

```
# 1-Import necessary libraries
import tkinter as tk
from tkinter import filedialog
from PIL import Image, ImageTk
import cv2
import numpy as np
from tensorflow import keras
from keras.models import load_model
from keras.preprocessing import image

# 2-Load the trained model
model = load_model('currency_detection_model.h5')
class_indices = {0: 'Fake', 1: 'Real'} # Define class indices

# 3-Function to predict currency given an image
def predict_currency(img):
    test_image = cv2.resize(img, (255, 255))
    test_image = np.expand_dims(test_image, axis=0)
    result = model.predict(test_image)
    prediction = class_indices[int(result[0][0])]
    return prediction

# 4-Function to handle image browsing
def browse_image():
    file_path = filedialog.askopenfilename()
    if file_path:
        img = cv2.imread(file_path)
        prediction = predict_currency(img)
        result_label.config(text=f"PREDICTION:   {prediction}")

# 5-Function to capture image from the camera
def capture_image():
    cap = cv2.VideoCapture(0)
    while True:
        _, frame = cap.read()
        cv2.imshow("Captured Image", frame)
        if cv2.waitKey(1) == 13:
            break
    cap.release()
    cv2.destroyAllWindows()

# 6-Preprocess the captured frame
    test_image = cv2.resize(frame, (255, 255))
    test_image = np.expand_dims(test_image, axis=0)
```

 # 7-Print the raw prediction result =
model.predict(test_image) print(f"Raw
prediction result: {result}")

 # 8-Convert the result to the predicted class
prediction = class_indices[int(result[0][0])]
print(f"Converted prediction result: {prediction}")
result_label.config(text=f"Prediction: {prediction}")

#9-Function to close the Tkinter window
defclose_window():
root.destroy()

 # 10-GUI setup
root = tk.Tk()
root.title("Currency Detection")
root.attributes('-fullscreen', True)

 # 11-Set the background color to beige
root.config(bg="#f5f5dc")

 # 12-Header widget
header_label = tk.Label(root, text="DETECTION OF INDIAN COUNTERFEIT CURRENCY USING CONVOLUTION NEURAL NETWORK", font=("Arial", 23,"bold"), bg="#f5f5dc")
header_label.place(relx=0.5, rely=0.1, anchor="center")

 # 13-Paragraph
paragraph_text = "WELCOME"
paragraph_label = tk.Label(root, text=paragraph_text, font=("Arial", 15), bg="#f5f5dc")
paragraph_label.place(relx=0.5, rely=0.25, anchor="center")

 # 14-Browse button
browse_button = tk.Button(root, text="Browse", command=browse_image, width=20, height=2, font=("Arial", 14, "bold"))
browse_button.place(relx=0.5, rely=0.35, anchor="center")

 # 15-Camera icon button
# Load a camera icon image
camera_icon_image = Image.open("camera.png")
camera_icon_image = camera_icon_image.resize((50, 50))
camera_icon_image = ImageTk.PhotoImage(camera_icon_image)
capture_button = tk.Button(root, image=camera_icon_image, command=capture_image, width=50, height=50)
capture_button.place(relx=0.5, rely=0.45, anchor="center")

#16- Result label
result_label = tk.Label(root, text="PREDICTION: ", font=("Arial", 18, "bold"), bg="#f5f5dc")

```
result_label.place(relx=0.5, rely=0.6, anchor="center")
```

 # 17-Exit button

```
exit_button = tk.Button(root, text="Exit", command=close_window, width=10,
font=("Arial", 12, "bold"))
exit_button.place(relx=0.95, rely=0.95, anchor="se")
```

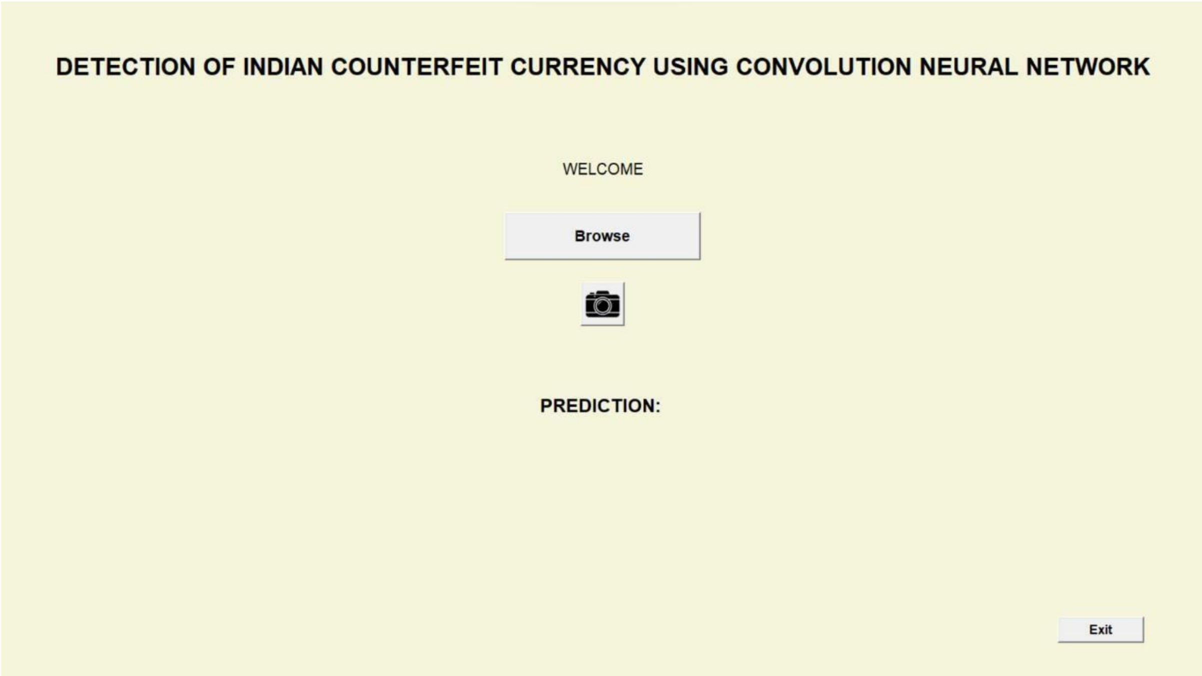
#18- Run the Tkinter event loop

```
root.mainloop()
```

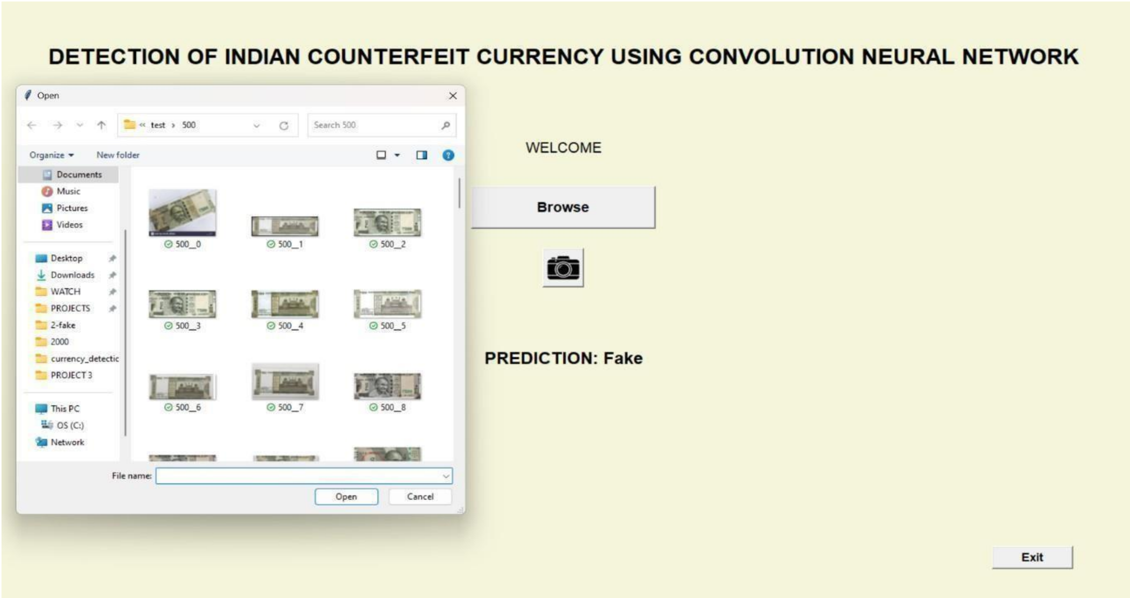
APPENDIX-B

SCREENSHOTS

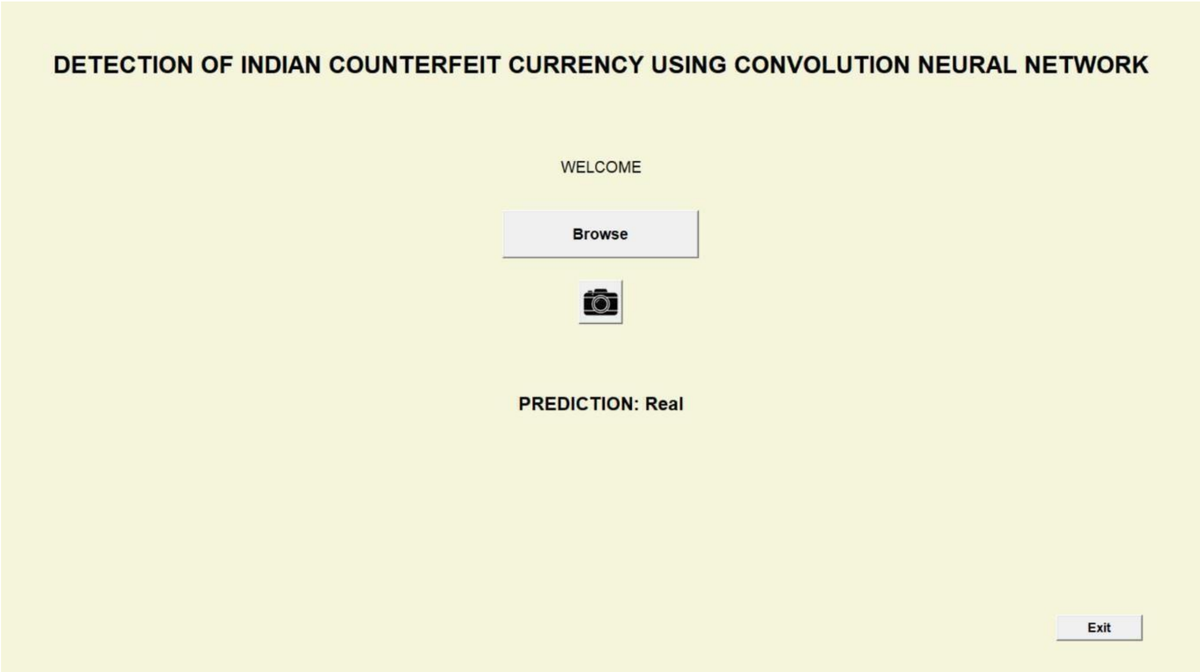
- **GUI Page:**

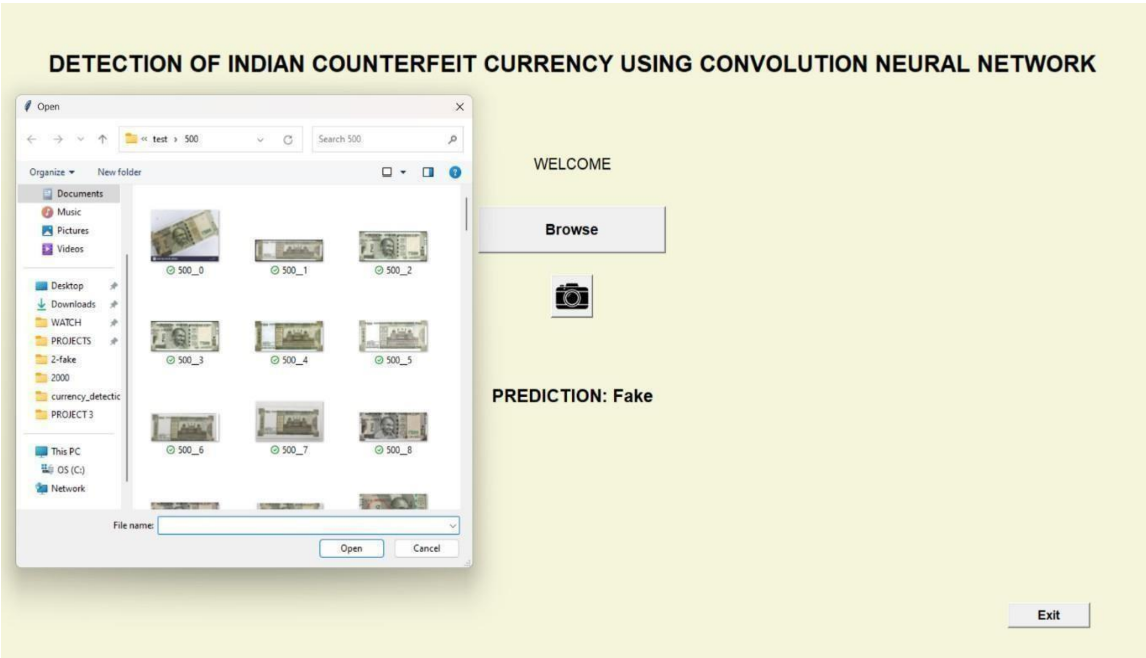


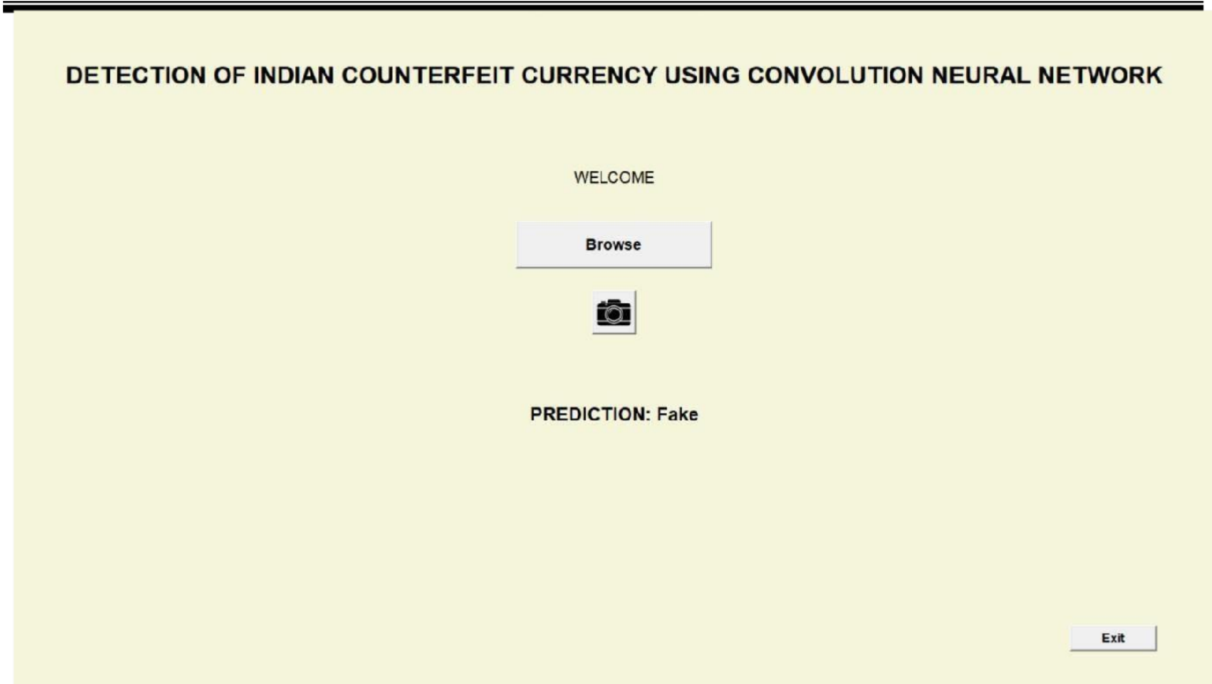
- **Uploading a 500Rs note from test dataset into "Browse" button:**



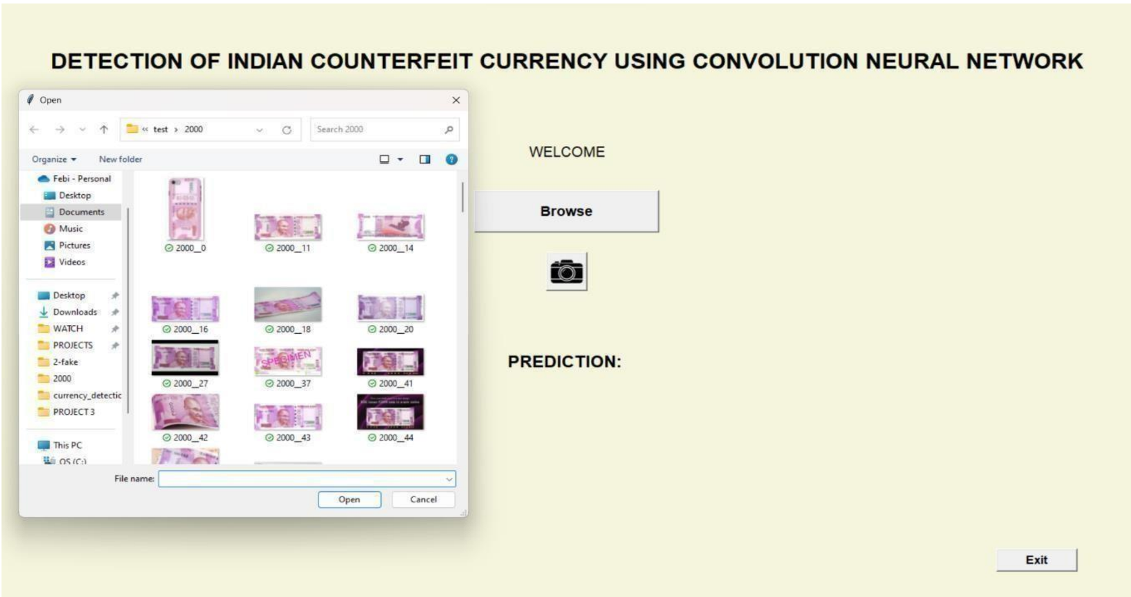
- **Prediction result:**



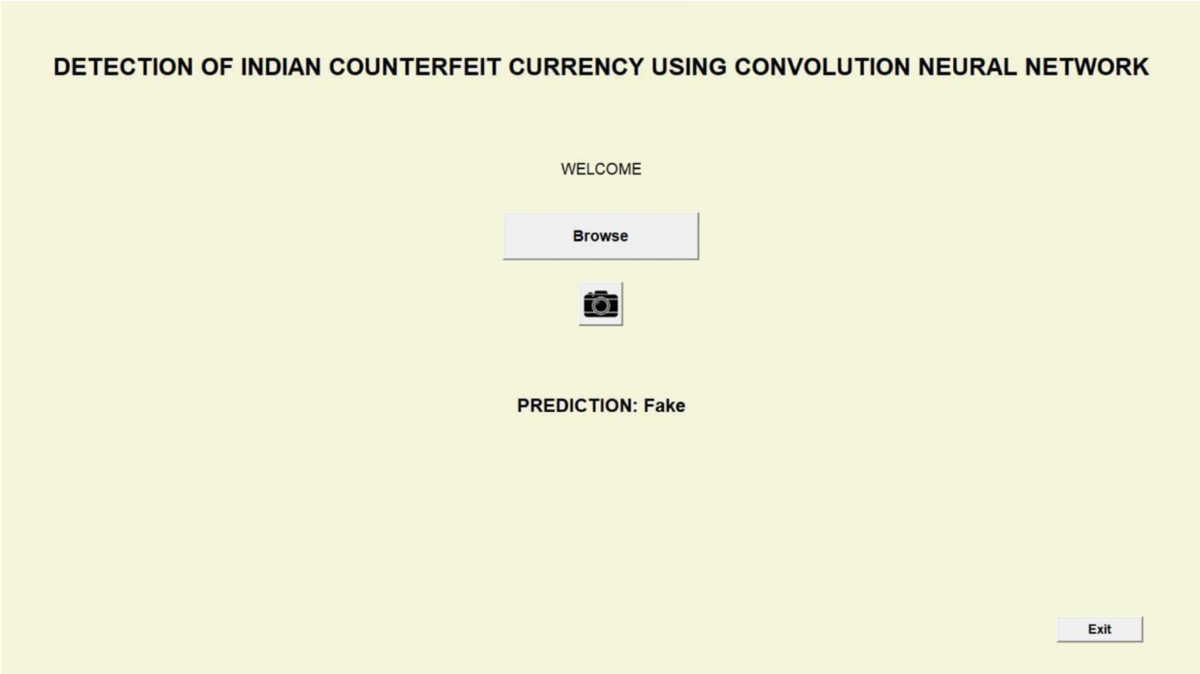


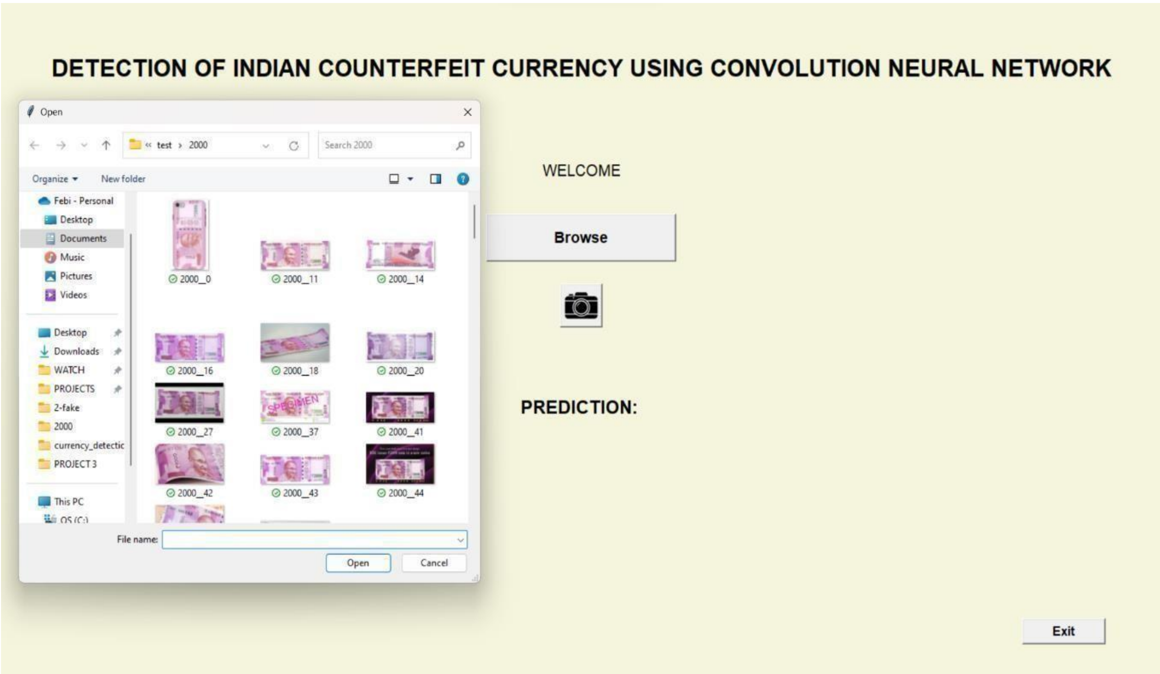


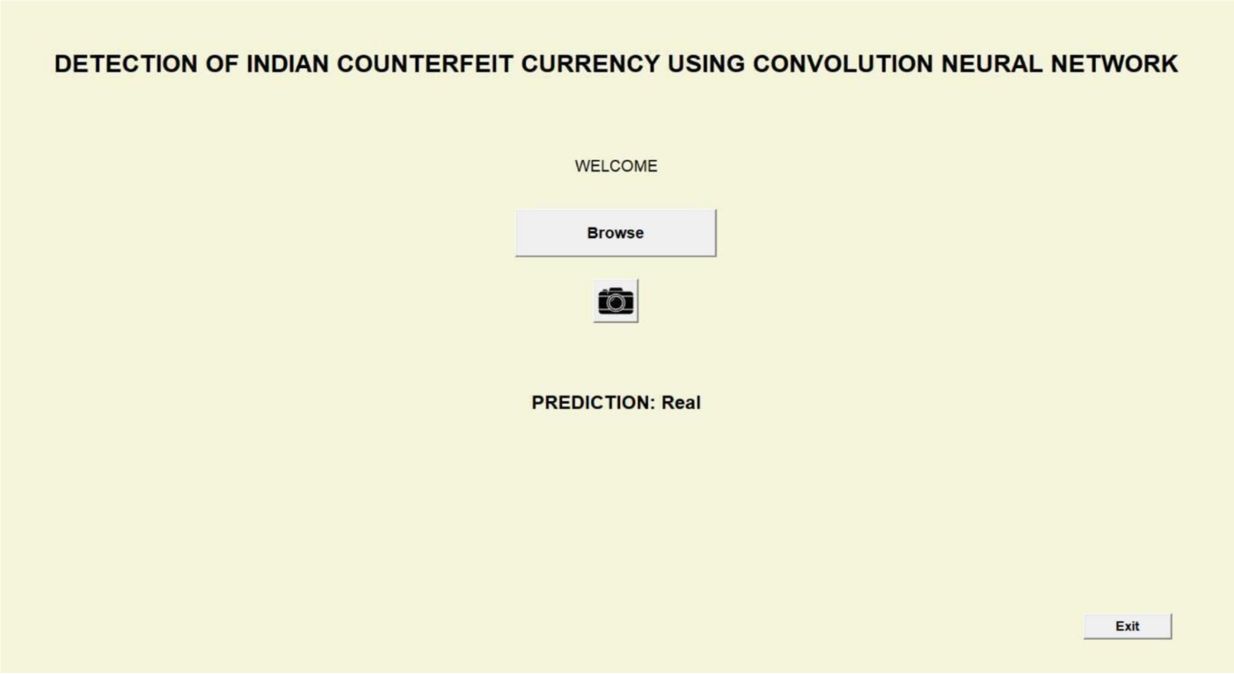
- **Uploading a 2000Rs note from test dataset into "Browse" button:**



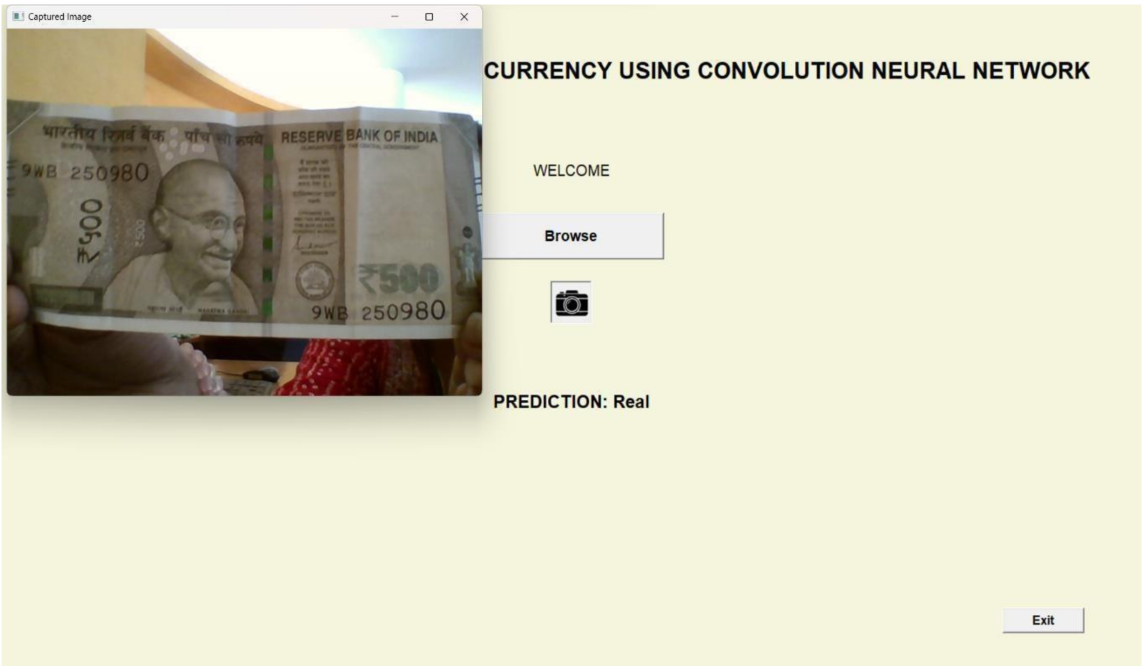
- **Prediction result:**



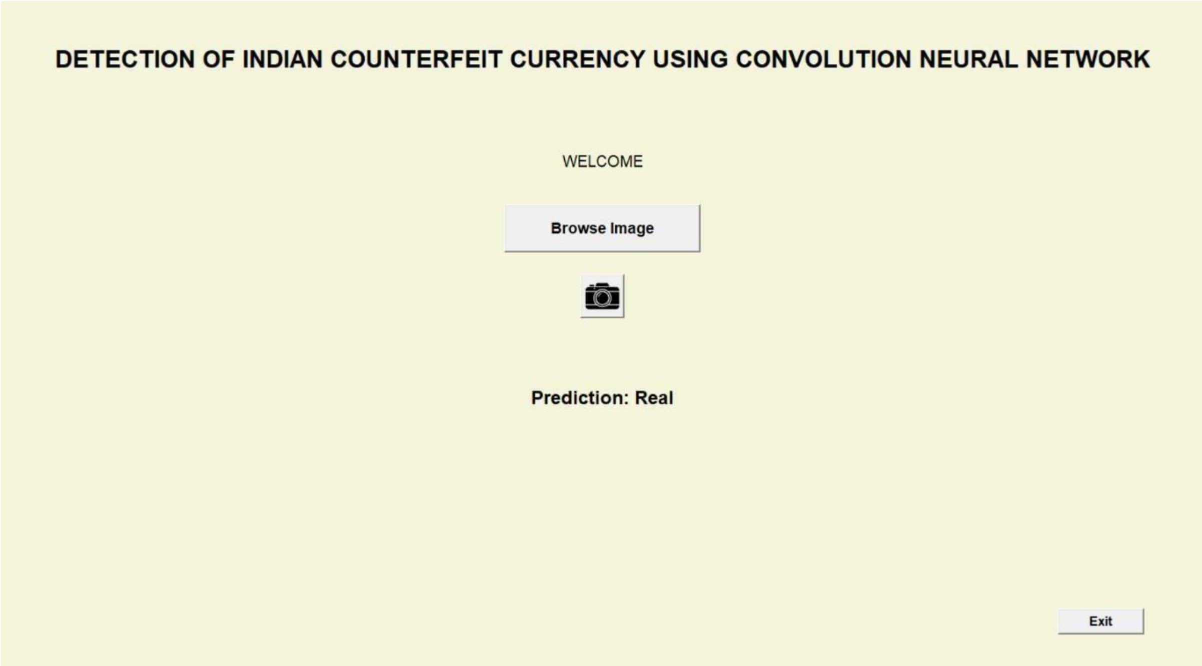




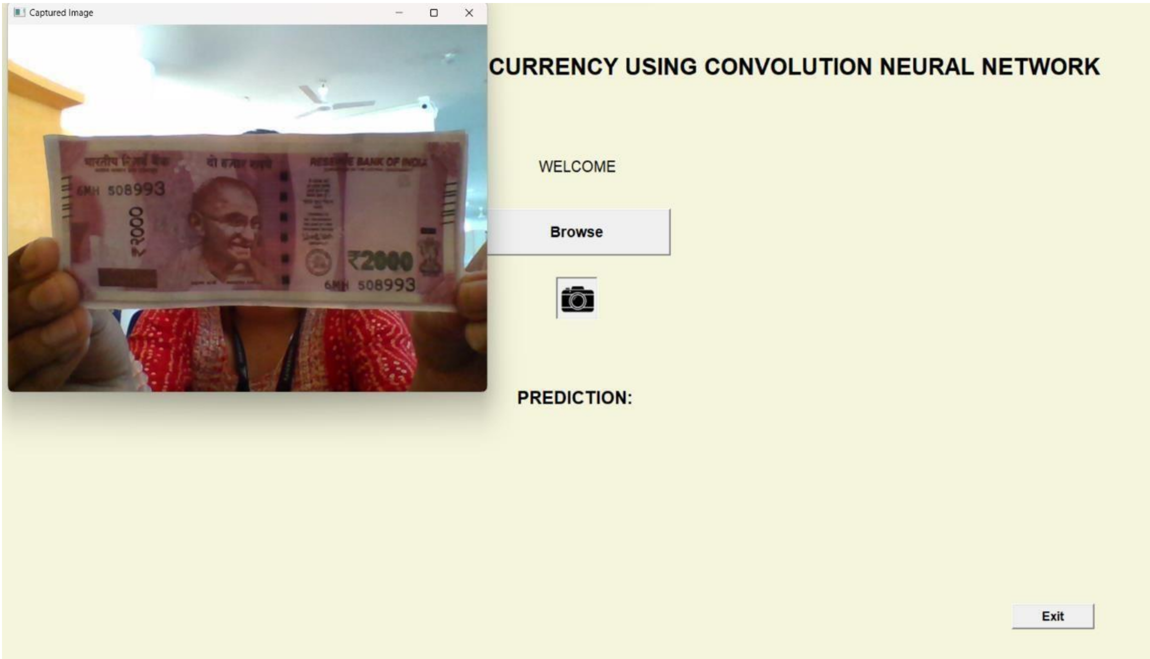
- **While clicking on the 'camera' icon, we can capture any 500 using the default camera of the system:**



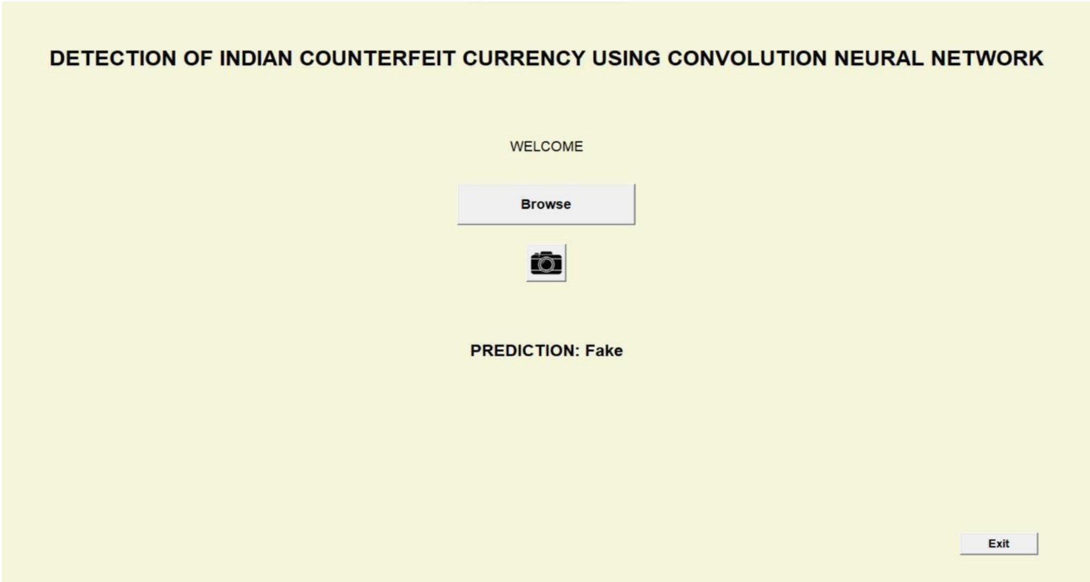
- **Prediction result:**



- **Similar step is followed for capturing a 2000Rs note as well:**



- **Prediction result:**



APPENDIX-C

ENCLOSURES

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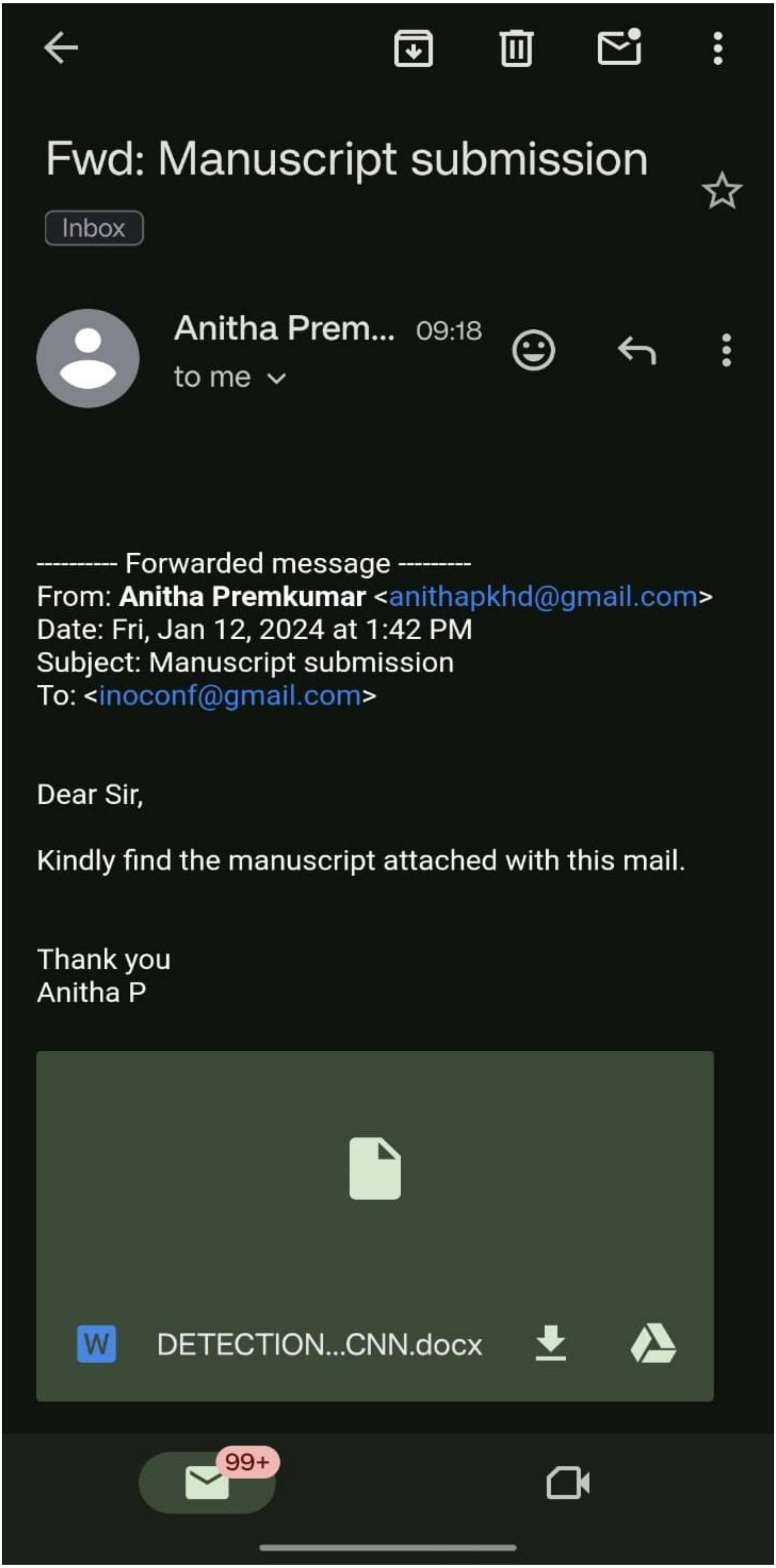
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