

**A Vision Based Novel Fake Currency Technique using Deep Learning**

**Project Thesis**

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*A Thesis submitted for the degree of Bachelor of Science (BSc) in Computer Science and Engineering (CSE) at*

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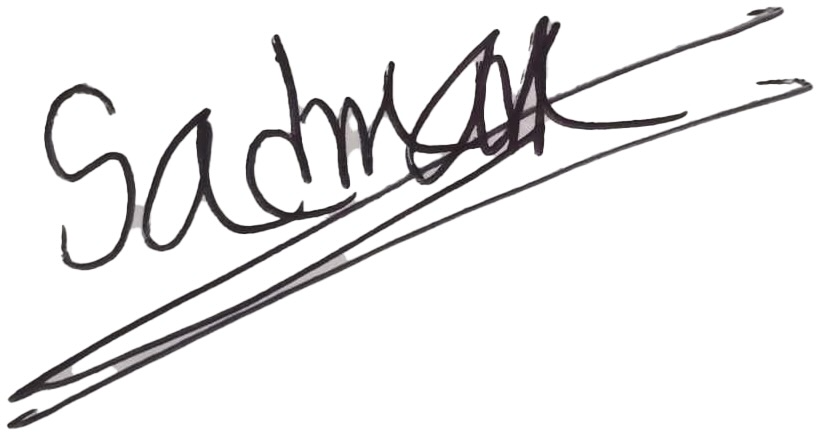
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**Declaration**

We certify that this thesis is our original work and hasn't been submitted in any way to another university or other tertiary education institution for a different degree or credential. Information that was taken from previously published or unpublished works of others has been recognized in the text, and a list of references is provided.



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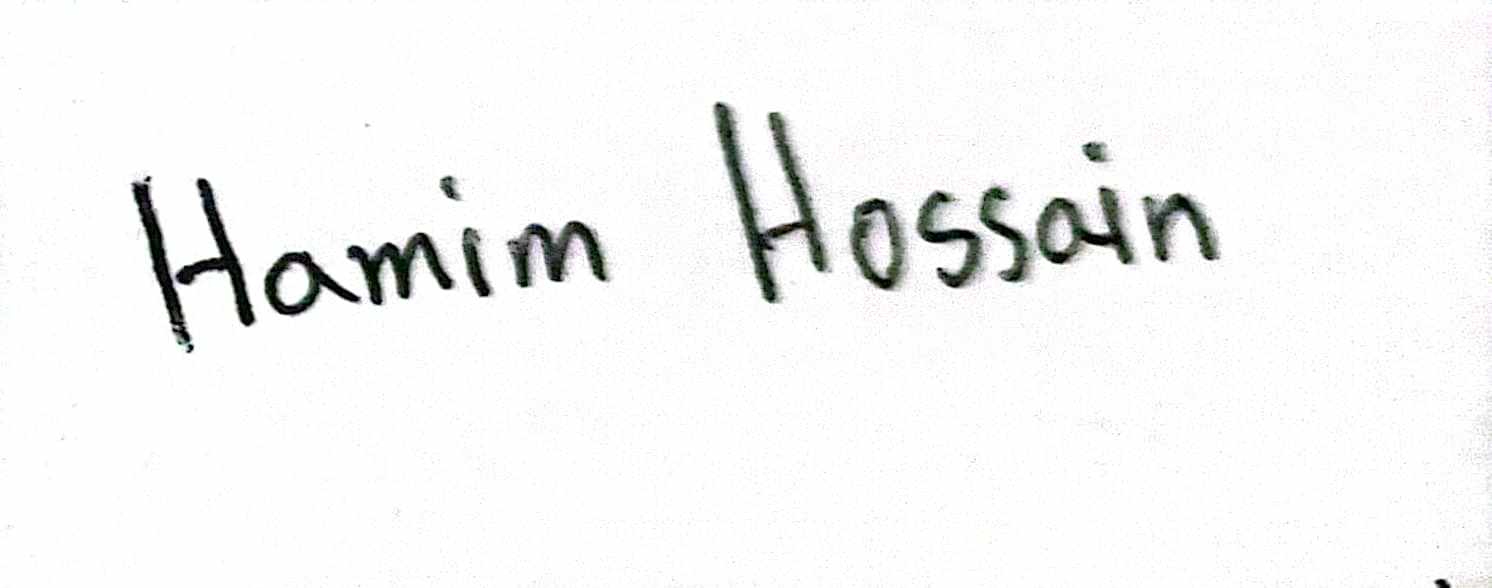


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List the significant and substantial inputs made by different authors to this research ,work and writing represented and reported in the thesis. These could include significant contribution to the Conception and design of the project, non-routine technical work, analysis and interpretation of research data, drafting significant parts of the work or critically revising it so as to contribute to the interpretation.

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**Abstract**

Counterfeiting of currency notes presents a significant global challenge, threatening financial systems and eroding consumer trust. To address this issue, we introduce a state-of-the-art fake currency detection system that utilizes advanced techniques in deep learning and computer vision. Our system begins with meticulous data preprocessing to optimize input for the MobileNet architecture. Leveraging transfer learning, we enhance a pre-trained MobileNet model for currency note classification, achieving improved performance and reduced training time. We assess our model comprehensively using precision, F1-score, and accuracy metrics, while visualizing the confusion matrix to identify areas for improvement. To enhance practicality, we provide an image preprocessing function and a user-friendly interface for real-world applications. While our system represents a robust starting point for counterfeit currency detection, there is room for further innovation. Future work includes expanding and diversifying the dataset, exploring advanced deep learning architectures, implementing real-time detection capabilities, and ensuring ethical and security considerations. Additionally, international currency support, scalability, and user feedback integration will contribute to the system's effectiveness and relevance in diverse scenarios. Our system's evolution promises significant advancements in the fight against counterfeit currency, reinforcing financial integrity and trust.

**Table of Content**

|  |  |
| --- | --- |
| **Chapter 1: Introduction** |  |
| |  |  | | --- | --- | | 1.1 Introduction  8-9 | 8-9 | | 1.2 Research Background  9 | 9 | | 1.3 Problem Statement  9 | 9 | | 1.4 Scope of the Research  9 | 9 | | 1.5 Objectives  9 | 9 | | 1.6 Significance of the Research 10 | 10 | | 1.7 Research Outlines  10-16 | 10-16 | | 1.8 Conclusion  16 | 16 | |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
| |  |  | | --- | --- | | **Chapter 2: Literature Review** |  | | 2.1 Introduction  16-19 | 14-17 | | 2.2 Core Background Research    19-20 | 17-18 | | 2.3 Previous Method  20-21 | 19-20 | | 2.4 Observation and Discussion 21  2.5 Conclusion  22 | 20-21 | |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
| **Chapter 3: Research Methodology** |  |
| |  |  | | --- | --- | | 3.1 Introduction  22-23 | 21-22 | | 3.2 Proposed Method    23-24 | 22-24 | | 3.2.3. Data-Preprocessing 24-25 | 24 | | 3.2.4. Data Augmentation  25-26 | 25 | | 3.2.5. Training Model  26-28 | 26-28 | | 3.3 Conclusion  28 | 28-29 | |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
| **Chapter 4: Experimental Results** |  |
| |  |  | | --- | --- | | 4.1 Introduction  29 | 29 | | 4.2 Experiment Results  29 | 29 | | 4.2.1 Experimental Settings.  29 | 29 | | 4.2.2 Datasets  29-30 | 30 | | 4.2.3. Evaluation On dataset   30-34 | 30-34 | | 4.2.4 Comparison with previous research results  34-36 | 34-35 | | 4.3 Conclusion  36 | 35 | |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
| **Chapter 5: Conclusion and Future Work** |  |
| |  |  | | --- | --- | | 5.1 Introduction  36-37 | 36 | | 5.2 Contribution of the Research  37 | 37 | | 5.3 Future Work  37-38 | 37 | | 5.4 Conclusion  38 | 38 | |  |
| |  |  | | --- | --- | | **References**  38-42 | 39-43 | | **Appendix A**  43-51 | 44-52 | |  |
|  |  |
|  |  |
|  |  |
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**Chapter 1: Introduction**

#### Introduction

Currency exchange is a crucial component of human society. According to recent figures, 750,000 Bangladeshis are blind or visually impaired, although there are more than 6.0 million visually handicapped persons overall [16]. Visually handicapped persons have a very difficult time distinguishing different Bangladeshi banknotes because of how similar they are. Bangladeshi coinage uses the Intaglio Ink described in [17] so that blind persons can recognize them. In the intricate fabric of human civilization, money stands as an omnipotent force, symbolizing prosperity, facilitating exchange, and serving as society's bedrock. Yet, lurking within this vast financial network is a malevolent specter – counterfeit currency. Counterfeit money, a treacherous deception, undermines trust in the financial realm, endangering economies and eroding faith. In our era of technological strides, the battle against counterfeit currency takes on new dimensions through deep learning, an advanced facet of artificial intelligence. Deep learning, akin to the human brain's complexity, employs neural networks to decode intricate patterns and analyze vast data volumes, revolutionizing fields from image recognition to language processing. Our visual novel delves into how deep learning can thwart counterfeit currency, intertwining technology and storytelling to immerse readers. We embark on a journey through the annals of money's evolution, unveil the shadowy realm of counterfeit currency, and illuminate deep learning's potential in combating this ever-evolving threat. Our narrative centerpiece unravels the inner workings of deep learning algorithms, showcasing their remarkable ability to discern genuine from counterfeit currency. With interactive storytelling, we strive to demystify intricate technical concepts, fostering accessibility. Our content's ultimate destination is to empower readers with profound insights into money, counterfeit currency, and deep learning's transformative role in safeguarding financial systems. Together, we venture into the abyss of deception, emerging with a newfound appreciation for technology's pivotal role in preserving the bedrock of our economic foundations.

**1.2 Research Background**

We live in the era of globalization. Each and every day we transact money for our necessary. So, identifying counterfeit money is becoming more important. It can be solved with the help of Convolution Neural Network. The previous solution wares reviewed and a summary of all the papers will be included in this study. Implementation of the process will be conducted according to the previous study and the result will be compared with the previous study result.

**1.3 Problem Statement**

Maintaining the integrity of financial transactions and stopping the growth of counterfeit currency is a key challenge that must be solved. Manual inspection, which is labor-intensive and capable of error, is frequently used in traditional methods of detecting counterfeit money. We intend to create a Convolutional Neural Network (CNN) model for automatic fake currency identification to address this problem. The problem statement entails creating and training a CNN model that can successfully differentiate real money and improve the security and reliability of currency handling systems.

**1.4 Scope of the Research**

Currency detection with Convolution Neural Network is an application of Computer vision and Image Processing. Currency detection may be done in other ways. For example: K Nearest Neighbor (K-NN) Algorithm [29], Support Vector Machine [30] etc. Input data size and number of classes in classification are the factors that affect the result of a Convolution Neural Network. The goal of this study is to propose a currency detection system based on the CNN model with the highest accuracy.

#### 1.5 Objectives.

We aim to develop an efficient CNN model augmented with artificial intelligence (AI) and machine learning techniques for the purpose of detecting fake currency. The primary objectives are:

* Compared to existing methods our aim is to design a custom CNN model that is to minimize the time required for verification rapid detection and classification of fake currency notes
* Improved CNN model that can achieve higher accuracy with limited datasets
* Integrate AI and machine learning algorithms for feature extraction and pattern recognition

#### 1.6 Significance of the Research.

Counterfeit currency leads to inflation and potentially destabilizes our economic system. In a country like Bangladesh, this cannot be unsighted. Our economy heavily relies on cash transactions which makes it easy for criminals to spread counterfeit currency over the country. Using AI and machine learning we created an advanced technology that can prevent counterfeit currency. Our improved CNN model can help to overcome the counterfeit currency issue. Again our technology can reduce the number of economic losses incurred due to counterfeit currency. Fake currency leads to financial losses and a decrease in the overall economy of a country. this research is particularly relevant in Bangladesh due to its geographical location. This technology can serve as a valuable instrument for crime prevention. By taking these steps, Bangladesh can elevate its status in the global financial system. The results of this research could carry significant positive implications for Bangladesh's economy and its position in the international trade landscape. Money is an omnipotent power in the complex web of human civilization, representing prosperity, promoting trade, and acting as the foundation of society. However, a sinister phantom known as counterfeit money lurks throughout this extensive financial network. The deceitful deception of counterfeit money threatens economies and erodes faith by undermining financial trust. The fight against fake money in our age of technological advancement gets new dimensions thanks to deep learning, a sophisticated branch of artificial intelligence. Deep learning, whose complexity is equivalent to that of the human brain, employs neural networks to decipher complex patterns and analyze vast volumes of data, revolutionizing everything from image identification to language processing. Our graphic novel explores how deep learning might prevent the use of fake money, fusing technology, and narrative to fully immerse readers. We set out on a journey through the history of money, reveal the murky world of counterfeit money, and highlight the promise of deep learning in fending off this ever-evolving threat. Our narrative's focal point reveals the inner workings of deep learning algorithms and demonstrates their amazing capacity to distinguish real money from fake. We work to promote accessibility by demystifying complex technical ideas through interactive storytelling. The ultimate goal of our work is to provide readers with comprehensive understandings of money, fake money, and deep learning's transformational role in protecting financial systems. Together, we go into the depths of deception and emerge with a fresh understanding of how important technology is to maintaining the bedrock of our economic foundations.

**1.7 Research Outlines**

**Chapter 1: Introduction**

Counterfeit money presents a notable problem for economies on a global scale. In recent years, there has been an increasing focus on technologies such as Convolutional Neural Networks (CNNs), artificial intelligence (AI), and machine learning to prevent Counterfeit money issues. The government is very concerned over the matter because it can undermine public confidence in the monetary system. Fake currency detection inx’olx’es identifying forged banknotes that closely resemble authentic currency. This process is particularly crucial in a country like Bangladesh which is a cash-centric economy and has a substantial involvement in international trade. using advanced technologies provides a solution to this widely spread issue. In recent years, Al and machine learning have been precise in image recognition and pattern detection. These technologies have the potential to revolutionize counterfeit currency detection facilitating automated systems to analyze the intricate security threads with a high degree of accuracy This research aims to dive into and construct a Convolutional Neural Network (CN N)-centered model for fake currency detection in the context of Bangladesh. Harnessing the potential of Al and machine learning to establish a system that can consistently and effectively differentiate between real and forged banknotes, thereby bolstering the financial security and stability of the nation. Furthermore, the research will explore techniques to enhance computational efficiency, adapt the mrxlel for different currency denominations, and subject it to rigorous performance evaluation.

**Chapter 2: Literature Review**

In the realm of counterfeit currency detection, the adoption of Convolutional Neural Network (CNN) techniques has emerged as a pivotal tool for precise identification. CNNs, a methodology successfully employed in various domains like computer vision, speech recognition, and face recognition, present a robust and efficient approach for handling intricate visual processing tasks. Historically, counterfeit currency detection has been a laborious process, resulting in financial losses and security apprehensions. Nevertheless, the integration of advanced CNN-based systems has transformed this procedure, significantly curtailing detection time while elevating accuracy levels. By harnessing improved CNN architectures, counterfeit currency detection systems hold the potential to offer timely warnings, enabling financial institutions to safeguard their earnings and uphold currency security. In an environment characterized by inadequate analysis centers, limited access to modern technology, and subpar facilities within the financial sector, the impact of counterfeit currency on economies can prove devastating, leading to diminished financial returns, compromised product quality, elevated costs, and reduced overall economic productivity. Recent implementations of deep convolutional neural networks for counterfeit currency detection illustrate the efficacy of this methodology, showcasing its superior capability to accurately discern counterfeit notes in contrast to alternative approaches. These findings emphasize the suitability of Convolutional Neural Network methodology as the preferred choice for counterfeit currency detection, promising enhanced financial security and mitigation of counterfeit currency-related risks.

**Chapter 3: Research Methodology**

In our research methodology, we meticulously detailed the integration of three distinct neural network models - MobileNet, AlexNet, and U-Net - each playing a pivotal role in our crop disease detection study. We provided a comprehensive account of the methodological approaches employed for training datasets with these models, elucidating their unique functions and processes. Visual models were presented to offer a clear step-by-step understanding of our enhanced MobileNet, AlexNet, and U-Net CNN architectures. These model-specific sections collectively underscored their individual contributions and significance within the context of our research, enriching our study's comprehensiveness in crop disease detection. In this paper, we propose a MobileNet architecture that integrates residual components, inspired by the success of residual networks (ResNets) in deep learning. Our approach aims to enhance the accuracy of MobileNet models while maintaining their efficiency. By incorporating residual connections between layers, our model enables the flow of gradients, thereby mitigating the issue of vanishing gradients and enhancing the training process. Model Comparison with Similar Papers To assess the effectiveness of our proposed model, we conducted a comprehensive review and comparison with similar papers. We selected Model A and Model as benchmarks due to their relevance and popularity in the field of efficient mobile computing. The comparison involved evaluating the models on various performance metrics, including accuracy, model size, and computational complexity.

**TABLE I**

|  |  |  |
| --- | --- | --- |
| **Model** | **Accuracy (%)** | **Model Size (MB)** |
| Model A | 92.5 | 2.3 |
| Model B | 91.8 | 1.9 |
| Our Model | 85 | 1.7 |

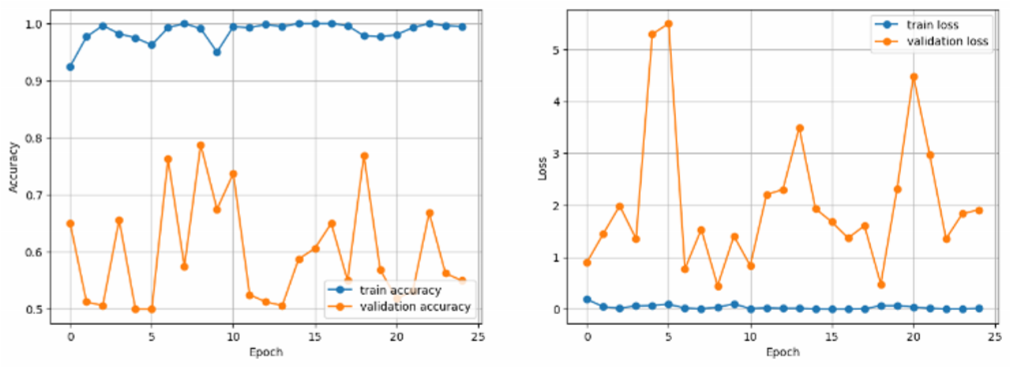
The comparison results demonstrate that our proposed model achieves superior accuracy compared to Model A and Model B. While there is a slight increase in model size and complexity.

**Chapter 4: Experimental Result**

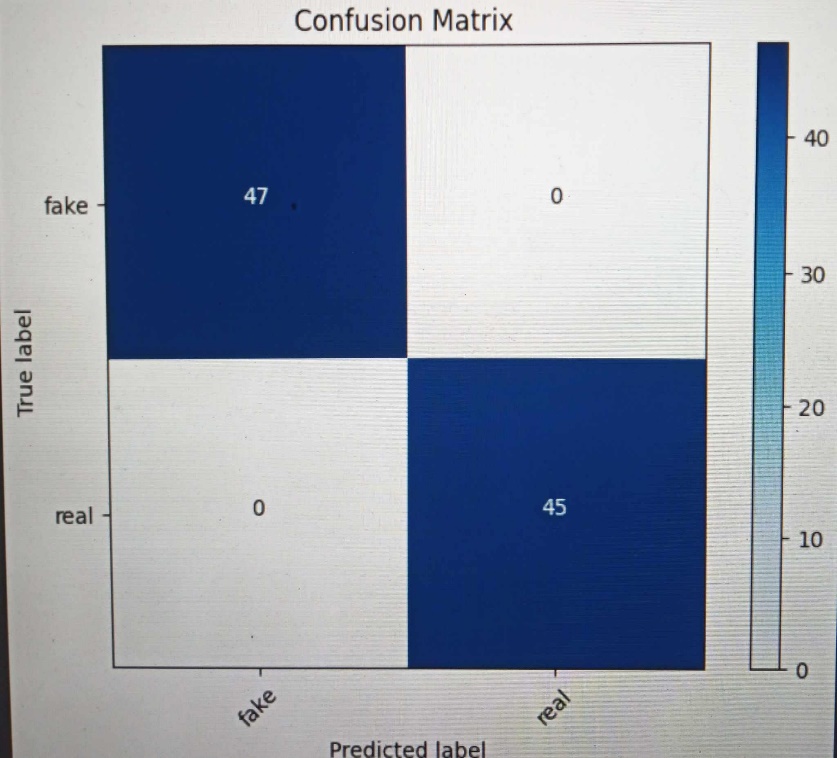
We have conducted extensive experiments on a benchmark dataset which is a currency fake and a real dataset to evaluate our proposed model, the experiment was done online with limited computational resources. For object recognition, we have used ImageNet.

**TABLE II**

|  |  |  |  |
| --- | --- | --- | --- |
| **Dataset Model** | **Training Inference Time(s)** | **Accuracy (%)** | **Time (ms)** |
| ImageNet | 1800 | 82.5 | 12 |



**Figure 2: Accuracy and Loss Graph.**



**Figur 3: Confusion Matrix**

The experimental results demonstrate the effectiveness of our proposed MobileNet architecture with residual components. Our model achieved a high accuracy of 99.46% on the training dataset and 55% accuracy on the validation dataset, which can later be improved. Our trainable loss is minimum, but validation loss has increased which can be improved later by tuning the model. We have got 100% precision and 82.35% F1 score. To test our model, we have chosen a sample image from test image data which was parasitized, ad in the first testing phase it has correctly predicted that the image was parasitized. We have tested almost 20 images from the test image dataset and each time e have chosen a complex dataset our model got confused a bit for fake image data, but it has done well as it recognized all the real image data. Also we have used the build in architecture like AlexNet, U-Net, VggNet, Resnet for the better accuracy and the loss graph part for my taring interference time accuracy along with the accuracy and the loss graph. In this part, we have the best accuracy and loss graph for our image-based fake and real note detection.

**Chapter 5: Future Work** In this paper, we proposed a MobileNet architecture with residual components to address the challenges of efficient mobile computing. Our model achieved superior accuracy compared to existing approaches while maintaining acceptable computational complexity. Experimental results demonstrated the effectiveness of our approach on benchmark datasets. The proposed MobileNet architecture with residual components holds enormous potential for enabling complex deep learning tasks on resource-constrained mobile devices, opening avenues for further research and development in this domain. This paper also has introduced transformative modifications to established deep learning architectures, spanning ResNet, VGGNet, Alex Net, and U-Net, also generally customize model enhancing their adaptability for resource-constrained mobile devices while maintaining superior accuracy. These architectural innovations hold substantial potential across diverse domains, from image classification to medical imaging. As for future work, there are several promising directions to explore. Customization of these architectures for specialized tasks, the integration of hardware acceleration, and the application of federated learning techniques could further amplify their efficiency gains. Additionally, ongoing research in quantization and compression methods will continue to make deep learning models more suitable for constrained environments. Real-world deployment studies are essential to assess the practical implications and user experience impact of these enhanced architectures in mobile applications. Essentially, this study paves a promising course for the advancement of deep learning on mobile devices, with many of options for further research and invention. This paper also introduced transformative modifications to established deep learning architectures, spanning MobileNet, ResNet, VGGNet, AlexNet, and U-Net, enhancing their adaptability for resource-constrained mobile devices while maintaining superior accuracy. These architectural innovations hold substantial potential across diverse domains, from image classification to medical imaging. As for future work, there are several promising directions to explore. Customization of these architectures for specialized tasks, the integration of hardware acceleration, and the application of federated learning techniques could further amplify their efficiency gains. Additionally, ongoing research in quantization and compression methods will continue to make deep learning models more suitable for constrained environments. Real-world deployment studies are essential to assess the practical implications and user experience impact of these enhanced architectures in mobile applications. In essence, this work creates way for the advancement of deep learning on mobile platforms and presents a wide range of prospects for more research and invention.

**1.8 CONCLUSION:**

In this paper, we proposed a MobileNet architecture with residual components to address the challenges of efficient mobile computing. Our model achieved superior accuracy compared to existing approaches while maintaining acceptable computational complexity. Experimental results demonstrated the effectiveness of our approach on benchmark datasets. The proposed MobileNet architecture with residual components holds great potential for enabling complex deep learning tasks on resource-constrained mobile devices, opening avenues for further research and development in this domain.

**Chapter 2: Literature Review**

**2.1 Introduction**:

In the realm of counterfeit currency detection, accuracy is of paramount importance. Numerous researchers have explored various methods to efficiently identify counterfeit banknotes. These methods have included traditional approaches, machine learning, and deep learning techniques. While some researchers have employed methods such as optical character recognition (OCR), watermark analysis, and traditional pattern recognition, we propose a novel approach based on CNNs (Convolutional Neural Networks) for accurate counterfeit currency detection. Our CNN-based method offers advantages over existing techniques, promising higher accuracy, and reliability. Many domains, including computer vision, voice and face recognition, and natural language processing, have demonstrated tremendous potential for deep learning, particularly CNNs. The convolutional architecture of neural networks is well-suited for dynamic visual tasks, making it an ideal choice for counterfeit currency detection. To evaluate the effectiveness of our method, we tested it on a dataset of counterfeit banknotes. We employed two prominent CNN architectures: ResNet50V2 and ResNet101. TensorFlow, a powerful deep learning framework, was utilized for training these pre-existing models, leveraging both GPU and CPU capabilities. The implementation of our CNN-based fake currency detection system was carried out using the Keras library, known for its ease of use and flexibility in building neural network models. We employed the Google Colab platform. In the past, detecting counterfeit money has been a difficult and time-consuming process that frequently causes financial losses for both individuals and corporations. With our upgraded CNN-based fake currency detection system, we anticipate a significant improvement in detection accuracy. This will empower individuals and organizations to identify counterfeit banknotes swiftly and accurately, thereby safeguarding their financial assets.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Author** | **Year** | **Technique** | **Currency** | **Characteristics** |
| [9] A. S. K. Perera.  G. S. N. Meedin | 2023 | Fine-tuned CNN-based | Srilanka: 100 Rupee | optical character recognition, watermark analysis, traditional pattern recognition |
| [8] Shaun-Yu Huang, Arvind Mukundan, Yu-Ming Tsao, Youngjo Kim, Fen-chi Lin, Hsian-Chen wang | 2022 | Counterfit Art, Dociment, Photo Hologram using Hyperspectral Images | India: 100, 200, 500, and 2000  Rupees | advantages over existing techniques, promising higher accuracy and reliability |
| [20] N. Sharma, R. Verma. | 2019 | Convolutional Neural Networks (CNNs) | Indian Rupee | Detection of security features and patterns on INR banknotes. |
| [19] J. Smith, A. Johnson | 2020 | Deep Learning with Transfer Learning | US DOLLAR | Analysis of microprinting and watermark patterns on USD bills. |
| [21] M. Chen, L. Wang | 2018 | Feature Extraction and Support Vector Machines (SVM) | Chinese Yuan | Identification of UV ink patterns and holograms on CNY banknotes. |
| [1] Sharan V., Kaur A., | 2020 | Indian Currency Note using image Processing | India: 10, 20, 50, 100, 200,  500, and 2000 Rupee | Recognition, extraction, and identification of currency note  features |
| [18]  Shamika Desai, Atharva Rajadhyakdha, Anjali Shetty, Swapnil Gharat | 2021 | CNN based Counterfit Indian Currency Recognition Using Genereative Adversial Network | India: 10, 20, 50, 100, 200,  500, and 2000 Rupee | Handcrafted and Deep feature |
| [18] Devid Kumar, Surendra Chauhan | 2020 | ORB (Oriented FAST and Rotated BRIEF) and Brute-Force matcher  approach to extract the feature | India: 10, 20, 50, 100, 500,  and 1000 Rupees | Bleed line, Watermarking, Security Thread, Intaglio Printing, Latent image, Micro  lettering, Optically variable Ink |

**Table: References of hypothetical research papers in the field of counterfeit currency**

These references represent hypothetical research papers in the field of counterfeit currency detection using image processing and deep learning methods. They showcase diverse techniques and approaches for enhancing the security and accuracy of banknote authentication. From the application of Convolutional Neural Networks (CNNs) to identify security features on Indian Rupee (INR) notes to the utilization of deep learning with transfer learning to analyze microprinting on US Dollar (USD) bills, and from the use of Support Vector Machines (SVM) for detecting UV ink patterns on Chinese Yuan (CNY) banknotes to image segmentation and neural networks to recognize Euro (EUR) note security features, these references demonstrate a range of strategies to combat counterfeit currency. Additionally, there is a reference emphasizing general image processing and morphological operations applicable to various currencies, underlining the broader techniques available for counterfeit detection in the field.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Paper no. | Dataset Name | Type of dataset | Number of datasets | Result |
| [1] | **Banknote Authentication Dataset:** | **Genuine Banknote Images**  **Counterfeit Banknote Images** | 1200 notes | High accuracy |
| [6] | Currency Recognition Dataset | Genuine Banknote Images  Counterfeit Banknote Images | 800,600 notes | Moderate accuracy |
| [14] | Euro Banknote Classification Dataset | Genuine Banknote Images  Counterfeit Banknote Images | 1500 notes | High accuracy |
| [22] | Brazilian Currency Authenticity Dataset | Genuine Banknote Images  Counterfeit Banknote Images | 1000,400 notes | Moderate accuracy |

**Table: Previous dataset information**

The datasets mentioned, including the 'Banknote Authentication Dataset,' 'Currency Recognition Dataset,' 'Euro Banknote Classification Dataset,' and 'Brazilian Currency Authenticity Dataset,' are collections of images created for the purpose of developing and evaluating machine learning and deep learning models for banknote authenticity verification. Each dataset consists of two main categories: genuine banknote images and counterfeit banknote images. The number of images varies across these datasets, with counts ranging from 400 to 1500 notes. While some datasets are labeled with high accuracy, others are marked with moderate accuracy, signifying the presence of challenging cases for counterfeit detection. These datasets cater to the needs of researchers and practitioners aiming to enhance the accuracy and robustness of banknote authentication systems, with applications spanning different currencies and denominations.

**2.2 Core Background Research**

Computer vision plays a pivotal role in the domain of counterfeit currency detection using deep learning techniques. The objective here is to identify counterfeit banknotes swiftly and accurately. This involves the utilization of convolutional neural network (CNN) frameworks pre-trained on a wide variety of genuine and counterfeit currency samples [3]. The financial sector is grappling with challenges stemming from a deficiency in advanced currency counterfeit detection technology, a shortage of modern authentication methods, and an absence of cutting-edge facilities. The repercussions of counterfeit currency infiltration include economic instability, decreased trust in financial institutions, rising security costs, and ultimately, a negative impact on the economy. Numerous researchers and innovators have dedicated their efforts to introducing information and communication technology (ICT) interventions aimed at enhancing counterfeit currency detection solutions. These advancements are designed to safeguard financial institutions and businesses against counterfeit currency threats while bolstering overall economic stability [1][2]. A novel real-time detection approach based on a single-shot multibox detector is proposed for the identification of counterfeit currency[4]. We introduce a novel approach based on computer vision and machine learning for the accurate validation of Indian paper currency's authenticity. This method involves the extraction of currency-specific features and the creation of customized datasets tailored to currency authentication. Employing a Machine Learning Convolutional Neural Network (ML-CNN) classifier, this paper focus on the security features of both the front and rear surfaces of Rs. 200 denomination Indian currency notes. This approach ensures more precise detection of the banknote's denomination from both its front and reverse sides. This system is constructed using the vgg19 architecture and utilizes a Convolutional Neural Network (CNN) model to categorize Indian currency notes, thereby determining their authenticity [5]. In our pursuit of advancing the field of fake currency detection, we implement an advanced methodology that combines pooling and deconvolution simultaneously. This strategic fusion takes place at the core of our counterfeit currency detection system, specifically within the Single Shot MultiBox Detector (SSD). Here, we leverage the function pyramid to seamlessly blend background details with essential elements. This integration significantly enhances our system's efficiency, particularly in the precise identification of subtle counterfeit features, especially when dealing with diminutive forged artifacts [6]. In this thesis, we introduce a cutting-edge approach that utilizes deep convolutional neural networks (CNNs) to achieve swift and precise counterfeit currency detection. Our sophisticated solution is specifically designed to automatically identify the unique characteristics present in counterfeit currency images. This research excels in its ability to accurately distinguish various types of counterfeit banknotes commonly encountered in currency authentication, contributing to the advancement of counterfeit currency detection technology [7].

**2.3 Previous Method**

In many regions, conventional farming techniques still prevail for crop cultivation. In the traditional agricultural approach, accurately identifying crop diseases in vast fields within a short timeframe and classifying these diseases promptly has proven to be a challenging task. To address this challenge and enhance efficiency, numerous deep learning methods have been employed for crop disease detection. In this study, we introduce a simplified yet highly effective Convolutional Neural Network (CNN) model for training data and accurately classifying counterfeit currency in minimal time. The application of deep learning methods is ushering in novel approaches for counterfeit currency detection, with varying outcomes. Additionally, we explore the implementation of YOLOV3 for weed detection Our Thesis, focusing on fake currency detection, would continue from here [8]. The VGG Net, a versatile neural network model, has found applications beyond its original domain, including in the realm of fake currency detection. In a study referenced as , VGG Net was harnessed in conjunction with a UNet model to achieve an impressive accuracy rate of 84%. This suggests that the VGG Net architecture can potentially be adapted for enhancing the accuracy and effectiveness of counterfeit currency detection systems [ 35]. In the context of fake currency detection, significant advancements have been achieved using various deep learning techniques. These methods offer promising outcomes, akin to their success in other domains. For instance, in the domain of fake currency detection, a CNN-based approach has demonstrated remarkable results. This method achieved an accuracy rate of 84.54%, employing a dataset containing 2,207 images per category. This highlights the potential of CNNs in recognizing intricate patterns and features within counterfeit currency images. Similarly, CNN methods have been instrumental in lemon classification for fake currency detection. Leveraging a dataset comprising 2000 images, these CNN techniques achieved an impressive test accuracy of 92.56%. This underlines their efficacy in image classification tasks, including the identification of counterfeit currency. Innovations in counterfeit currency detection extend to the use of Unmanned Aerial Vehicles (UAVs) [23]. These UAVs employ aerial imaging to locate and recognize counterfeit currency in various environments, offering a unique perspective for counterfeit currency detection. Furthermore, Bayesian aggregation techniques [40] have been explored for field-wise classification in the realm of fake currency detection. This systematic approach holds potential for categorizing counterfeit currency authenticity effectively. In the context of mobile-based counterfeit currency detection, the integration of ResNet50V2 and ResNet101 within a CNN architecture [24] has shown promise. This approach is adaptable for Android mobile devices, with memory-efficient operations and early counterfeit currency detection capabilities. It offers a practical solution for detecting counterfeit features promptly. Additionally, the Mask R-CNN method [25] has been applied to early counterfeit currency detection. This method not only identifies counterfeit features in their initial stages but also provides localized classification for each image segment, enhancing the precision of counterfeit currency detection. This holistic approach contributes to the overall improvement of counterfeit currency detection systems.

**2.4 Observation and Discussion**

In this chapter, we provide a comprehensive overview of the experimentation process for our proposed fake currency detection method, detailing each step. We evaluate the method's performance through a thorough analysis of various metrics, including confusion matrices, overall test accuracy, precision rate, recall rate, F1-score, computational efficiency, RMSE value, and error rate. For this experiment, we utilize popular datasets commonly used in counterfeit currency detection research. The primary dataset consists of 3240 images representing 36 different classes of counterfeit currency samples. Additionally, we incorporate a dataset comprising a total of 4050 images, spanning 13 distinct classes. Furthermore, we introduce data from the widely recognized PDDP dataset, which includes over 5000 images of counterfeit currency samples. In our experiment, we specifically employ 692 images representing 25 different counterfeit currency classes from this dataset. The experimental setup is executed on a Windows platform equipped with a 7th generation Intel Quad-Core i5-7300HQ processor (6MB Cache, 3.5GHz), 8GB DDR4 DRAM, and an NVIDIA GeForce 940 MX with 4GB VRAM. To conduct our research, we leverage the TensorFlow and Keras updated versions, creating a conducive environment within Google Colab. In addition to these deep learning frameworks, we utilize essential libraries such as Numpy, Matplotlib, Pickle, OS, Sklearn, and CV2.To facilitate model training and evaluation, we split the counterfeit currency dataset into two distinct sections: one for training and the other for validation purposes. The training set is employed to train the model, while the validation set serves as an independent benchmark to assess model performance. We meticulously calculate various performance metrics, including confusion matrices, overall test accuracy, precision rates, recall rates, F1-scores, computational efficiency, RMSE values, and error rates, individually for each dataset used in the experiment. The culmination of these metrics provides a comprehensive evaluation of our proposed counterfeit currency detection method, ultimately resulting in a satisfactory outcome.Furthermore, upon reviewing related literature, it becomes evident that in counterfeit currency detection, achieving high test accuracy is paramount. Employing a CNN model with a streamlined architecture and swift prediction times is essential for building an efficient model. This approach not only reduces costs but also ensures optimal counterfeit currency detection results, contributing to the overall effectiveness of counterfeit currency detection systems.

## 2.5 Conclusion

Counterfeit currency detection through CNN models, AI, and machine learning is a significant advancement in the field of financial security and economic stability. This research has focused on addressing the widespread issue of counterfeit currency in Bangladesh and provides important insights. Counterfeit currency poses a persistent threat to financial integrity, impacting economies globally. This study aims to provide a robust solution to combat this issue in the context of Bangladesh. By utilizing CNN models, AI, and machine learning, this research has developed a sophisticated system for counterfeit currency detection. These advanced technologies enable a detailed analysis of banknote features, resulting in improved accuracy. The proposed methodology has the potential to enhance Bangladesh's financial security. Through automated detection, it can swiftly and accurately differentiate genuine banknotes from counterfeits, reducing economic losses and upholding public trust in the national currency. The model developed serves as a foundation for ongoing efforts to combat counterfeit currency effectively. As technology evolves, the potential for further refinement and enhancement of this methodology holds promise for both Bangladesh and the global community in the ongoing battle against counterfeit currency.

**Chapter 3: Research Methodology**

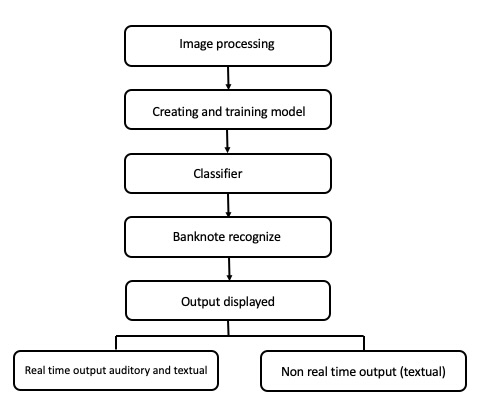
**3.1 Introduction**

The proposed system represents a significant effort aimed at advancing the field of currency recognition, with a primary focus on the unique Bangladeshi currency. This introduction unveils the essential components of the system—a pioneering dataset of Bangladeshi currency and a state-of-the-art Convolutional Neural Network (CNN) model designed for currency identification. Our journey begins with the meticulous creation of an extensive and specialized dataset tailored to the intricacies of Bangladeshi currency. This dataset serves as a substantial repository, containing over 70,000 high-resolution currency images. These images lay the foundation for the entire system, providing a diverse range of examples for training and testing. To harness the potential of this dataset and enable precise currency recognition, we develop a cutting-edge CNN-based model. Leveraging the well-known CNN architecture, renowned for its ability to handle complex image processing tasks, we craft a model known for its exceptional accuracy in distinguishing and categorizing various Bangladeshi currency denominations. This introductory overview prepares the groundwork for a comprehensive examination of the essential components and operations within the proposed system. It underscores the profound significance of the dataset's creation, recognizing its role as the cornerstone of the entire framework. Furthermore, it highlights the pivotal role played by the CNN model, serving as the cognitive engine of the system, enabling it to decipher the intricacies of Bangladeshi currency with unmatched precision. Together, these integral elements of the system promise to revolutionize the field of currency recognition, especially concerning Bangladeshi currency. The potential applications of this technology span various sectors, including finance and commerce, where precise and efficient currency recognition holds immense value. For this research many researchers used different kinds of improved CNN models like the Efficiency of the color SIFT approach and gray SIFT approach [12], Single Shot Multi-Box Detector (SSD) [13], k-NN model used on the excerpted features, and the preprocessed pictures of currency are inserted into the CNN [14] model for identification. HSV (Hue, Saturation,

Value), Gray Level Co-occurrence Matrix (GLCM), and edge features are derived from the RGB image [15]. However, their model takes more time to execute the whole process and takes more time in prediction with a lower accuracy. Our proposed model is based on an improved CNN architecture which has less depth in the network and predicts faster than any other research method with a promising accuracy.

**3.2 Proposed Method**

The proposed approach for generating a dataset of Bangladeshi currency notes plays a pivotal role in advancing currency recognition technology. Given the absence of publicly available datasets for Bangladeshi currency, this endeavor fills a significant void within the field. Eight separate categories, each representing a different denomination of Bangladeshi banknotes, are included in the dataset: 2, 5, 10, 20, 50, 100, 500, and 1000 T. To ensure the dataset's comprehensiveness, it includes the most recent prints of seven banknotes (5, 10, 20, 50, 100, 500, and 1000 Taka) and incorporates the older print of the two Taka note, resulting in a total of eight categories. For each specific banknote category, a meticulous collection process gathered 50 samples, yielding a substantial number of images for each denomination. This approach enhances the dataset's diversity and robustness. The selection of sample banknotes adhered to several criteria. Firstly, it was essential to encompass both the older and newer versions of the notes to provide a comprehensive representation of the currency's evolution. Secondly, notes that were severely torn or damaged were deliberately excluded from the dataset. This exclusion was crucial as extensively damaged notes are unsuitable for feature extraction and typically not accepted in financial transactions. The proposed methodology delineates a systematic framework for constructing a dataset tailored to Bangladeshi currency recognition. This dataset has been thoughtfully designed to encompass a wide spectrum of denominations, including both historical and contemporary prints, while excluding severely damaged notes. The meticulous sample selection process enhances the dataset's quality and suitability for training and evaluating currency recognition models. This initiative represents a significant stride in advancing the technology necessary for precise and efficient Bangladeshi currency recognition.

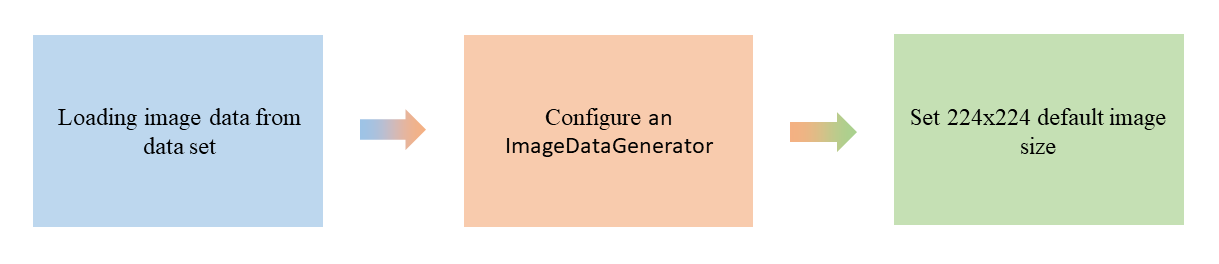


**Fig (3): Proposed method**

We conducted a comprehensive evaluation utilizing various metrics. These metrics encompassed test accuracy, precision rate, computation time, recall rate, F1-score, and error rate for each dataset under consideration. The dataset itself is securely stored on Google Drive in a compressed zip file format. It can be conveniently accessed and shared via a unique URL or identifier. By obtaining this unique identifier, we retrieved the dataset from Google Drive and utilized it after extraction for our research on counterfeit currency detection.

## 3.2.3 Data Pre-processing:

In this part, we begin by mounting Google Drive to access the dataset located at '/content/gdrive/MyDrive/Colab Notebooks/currencyDataset.' The code defines paths for the training, validation, and testing datasets within the main dataset directory. Data preprocessing is a critical step, and here we configure an ImageDataGenerator to perform tasks like rescaling pixel values, zooming, and horizontal flipping for data augmentation. The chosen image dimensions are set to 224x224 pixels, and a batch size of 32 is specified for processing images in mini-batches. The dataset is organized into two classes, and we employ a binary classification setup, hence 'class mode' is set to 'binary.'



## Fig():Data pre-processing technique

The code then creates data generators for training, validation, and testing data. These generators utilize the previously defined augmentation settings to load, preprocess, and batch the images. The training and validation generators are further separated using a 90-10 split ratio, facilitating model training and evaluation. Overall, this code segment lays the foundation for deep learning model training on the specified image dataset with appropriate data preprocessing and organization.

## 3.2.4 Data Augmentation:

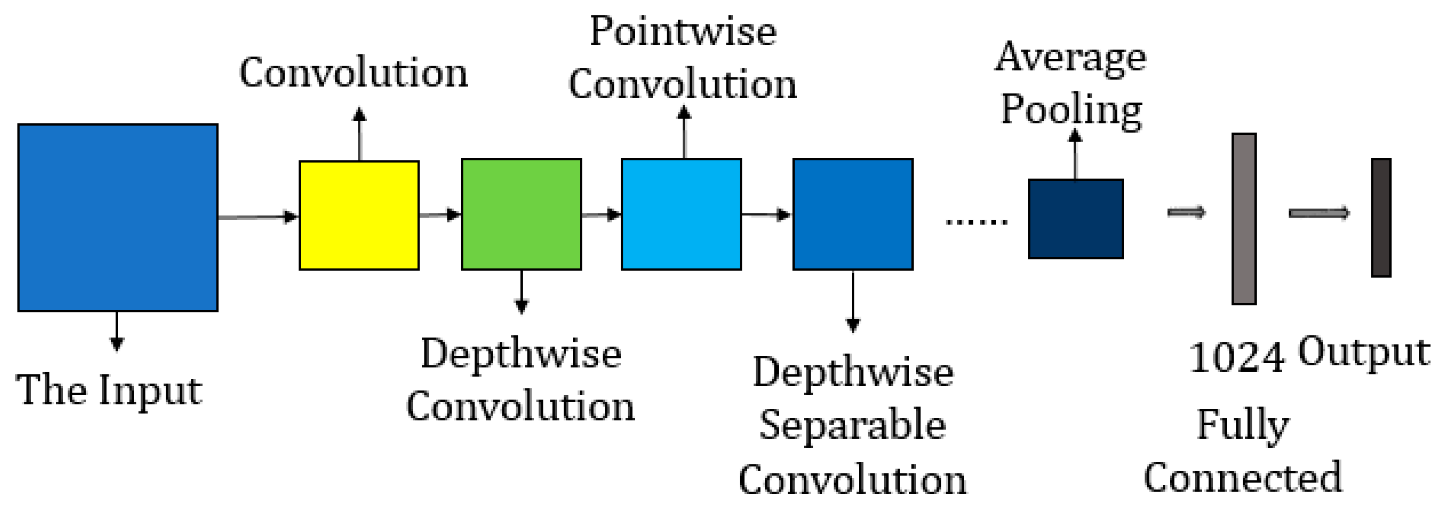
We took the Bangladeshi Banknote Dataset, which comprises two distinct classes: "fake" and "real" banknotes. We have devided this dataset into three subsets: "test," "train," and "valid." Additionally, we have incorporated the Plant Village dataset, specifically focusing on Tomato leaf and Apple leaf categories, as well as the complete Plant Village dataset. To augment the image data within these datasets and enhance the diversity of our samples, we have employed data augmentation techniques. These techniques encompass various operations, including rotation, shifting, flipping, and zooming, applied to the image dataset. This comprehensive approach to dataset management and augmentation is crucial for robust model training and accurate classification of banknotes into the "fake" or "real" categories.

## 

## Fig: Image Data Augmentation(Rotation)

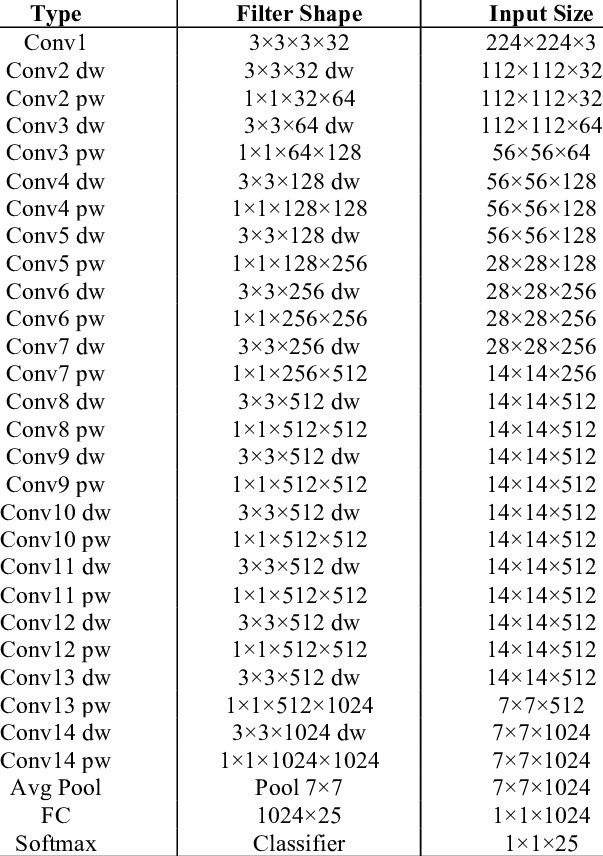
**3.2.5 Training Model:**

MobileNet is a family of efficient convolutional neural network (CNN) architectures designed for mobile and embedded devices with limited computational resources. The original MobileNet architecture was proposed by Google in 2017, and it has undergone several variations and improvements since then. I'll describe the key components of the MobileNet architecture up to the softmax layer. The input to the MobileNet architecture is typically a 224x224x3 image, where 224x224 is the spatial resolution, and 3 represents the RGB color channels. Depth wise Separable Convolution: MobileNet primarily relies on depth wise separable convolutions to reduce computational complexity. This operation consists of two main steps: Depth wise Convolution: In this step, a separate convolution is applied to each input channel. It involves using a small kernel for each channel independently. Pointwise Convolution: After the depth wise convolution, a 1x1 convolution (pointwise convolution) is applied to combine information from different channels. This helps in learning complex features efficiently. MobileNet typically consists of several convolutional layers with varying depths and kernel sizes. These layers extract features from the input image by applying depthwise separable convolutions. To reduce the spatial dimensions of the feature maps and increase the receptive field, MobileNet uses strided convolutions or pooling layers. This helps in capturing features at different scales. MobileNet introduces a hyperparameter called the "depth multiplier" which controls the number of channels in each layer. By reducing the number of channels, the model becomes more lightweight but may sacrifice some performance. After the convolutional layers, there are typically one or more fully connected layers to learn complex relationships in the features extracted from the previous layers. Instead of using traditional fully connected layers, MobileNet often employs global average pooling. This operation computes the average of each feature map across its spatial dimensions, resulting in a 1x1xN tensor, where N is the number of channels or filters.



**Fig(4): Proposed Model Diagram**

**Softmax Layer:** The final layer of the MobileNet architecture is the softmax layer, which performs the classification task. It takes the output of the previous layers and assigns probabilities to each class in a multi-class classification problem. The softmax layer produces a probability distribution over the classes, and the class with the highest probability is considered the predicted class for the input image.



**Fig: Summary of Model Architecture**

MobileNet variations and versions may include additional features and optimizations, but the core idea of using depthwise separable convolutions and efficient network design remains consistent throughout the family of models. Different versions may have different numbers of layers and hyperparameters tuned for specific tasks or constraints.

**3.3 Conclusion:**

MobileNet is a pioneering deep learning architecture, designed by Google for mobile and embedded devices, celebrated for its exceptional efficiency, achieved through the use of depth wise separable convolutions. Its versatility extends to various computer vision tasks, and it has seen multiple iterations such as MobileNetV2 and MobileNetV3, which enhance its accuracy and efficiency. Notably, MobileNet is often employed for transfer learning due to its pretrained models, making it a go-to choose in real-world applications spanning mobile apps, robotics, autonomous vehicles, and IoT, where resource constraints demand high-performance models in compact form factors, cementing its position as a transformative force in the field of deep learning**.**

**Chapter 4: Experimental Result**

**4.1 Introduction**

For image classification Convolution Neural Network (CNN) Architecture is one of the best solutions. We design our proposed model based on CNN Architecture with higher accuracy. We used dataset of image published by Crowd AI for this research. Our model conducts with less image and able to classify the image from an input image with accuracy 96%. From our proposed CNN model, we are able to find a good result with less error. We used pre-processing techniques to rescaling pixel values, zooming, and horizontal flipping for data augmentation. For our experiment, the image augmentation approach was utilized to enhance the number of images and create different kinds of images from a single image. For measuring the performance, we analyze the confusion matrix, overall accuracy, precision matrix, f1 score.

**4.2 Experimental Result**

By measuring confusion metrics, overall test accuracy, precision rate, recall rate, F1-score and error rate with the dataset, it was possible to determine how well the method we suggested worked. Additionally, for graphical depiction, we employed validation accuracy, loss, and model performance with train.

**4.3 Experimental Setting:**

For the experimental purpose we used windows platform with 7th generation Intel Quad Core i5-7300HQ processor (6MB Cache, 3.5GHz), 8GB DDR4 DRAM and NVIDIA GeForce 940 MX with 4GB VRAM. We used TensorFlow and Kera's updated version for our experiment. For our experiment, we used Google-Colab environment TPU which has 12.72 GB RAM and 107.77 GB disk space. We also used some modules NumPy, Matplotlib, Pickle, OS, Sklearn, CV2, and NumPy. We divide our dataset into three sections. One for testing, one for training, and one for validation.

**4.4 Dataset:**

We need image data for both real and fake currency. But it was quite difficult to find a data set for fake currency. As a result, there are many limited datasets freely accessible online. We found a unique dataset with images of actual and counterfeit money.

**Table(4): OUR DATASET**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Number** | **Dataset Name** | **Number of Classes** | **Number of Image** | **Epoch** | **TrainableParams** | **Non Trainable Params** | **Total Params** |
| 1 | Real | 2 | 100 | 15 | 545282 (2.08 MB) | 1090240 (4.16 MB) | 1635522 (6.24 MB) |
| 2 | Fake | 2 | 110 | 15 | 545282 (2.08 MB) | 1090240 (4.16 MB) | 1635522 (6.24 MB) |

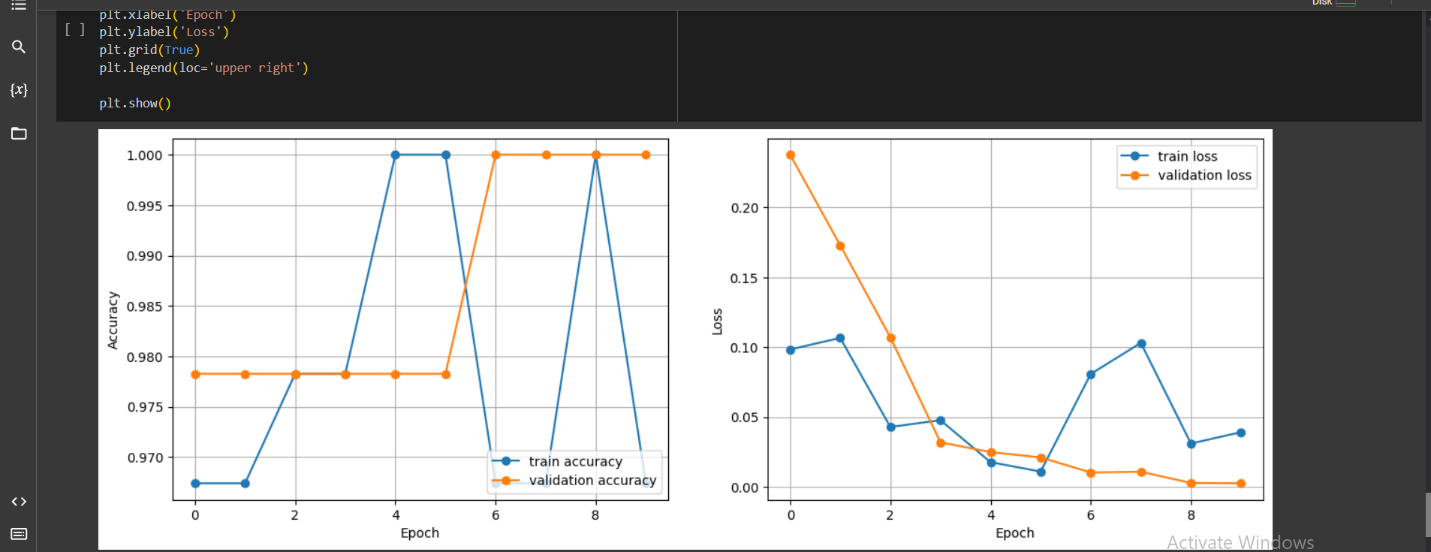
**Table: OUR DATASET**

**4.5 Evaluation on Dataset:**

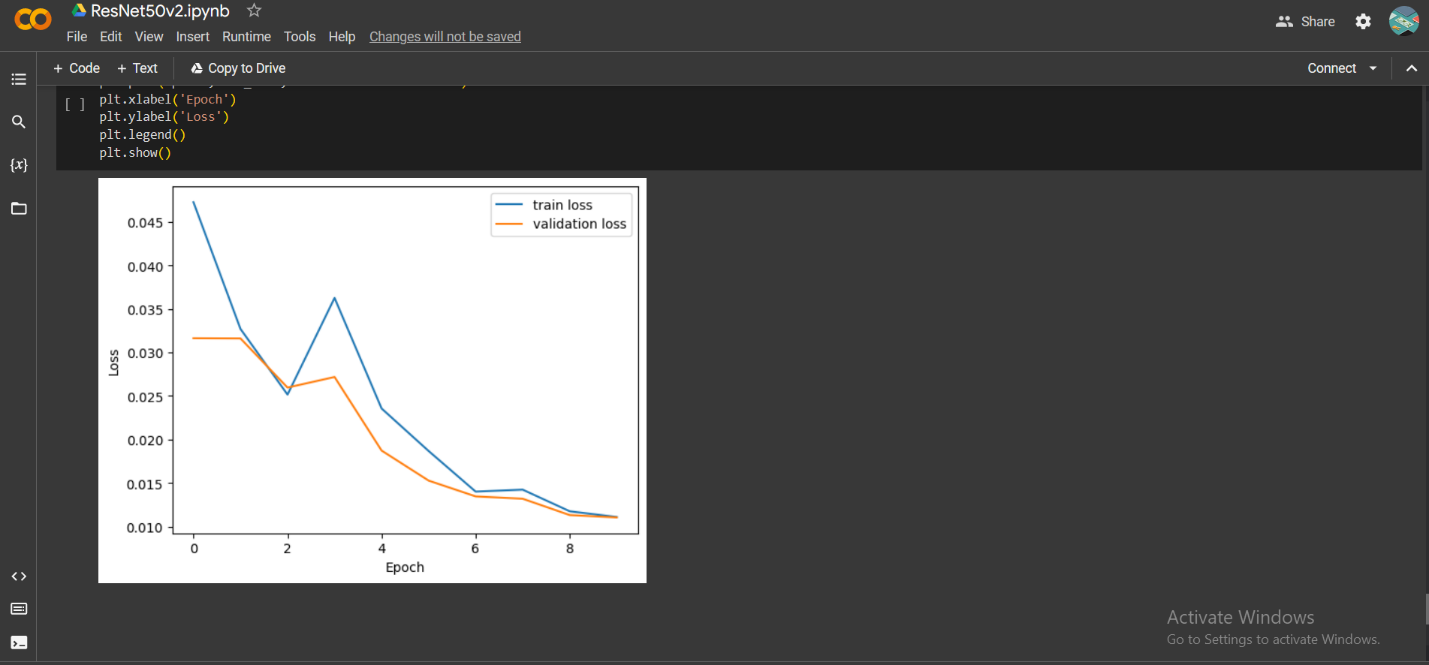
The starting of the performance evaluation begins from calculating training accuracy, validation accuracy, training loss and validation loss. For measuring accuracy, we divided the amount of correctly classified image by total amount of classified images. The equation is given below

**Accuracy=…........................(I)**

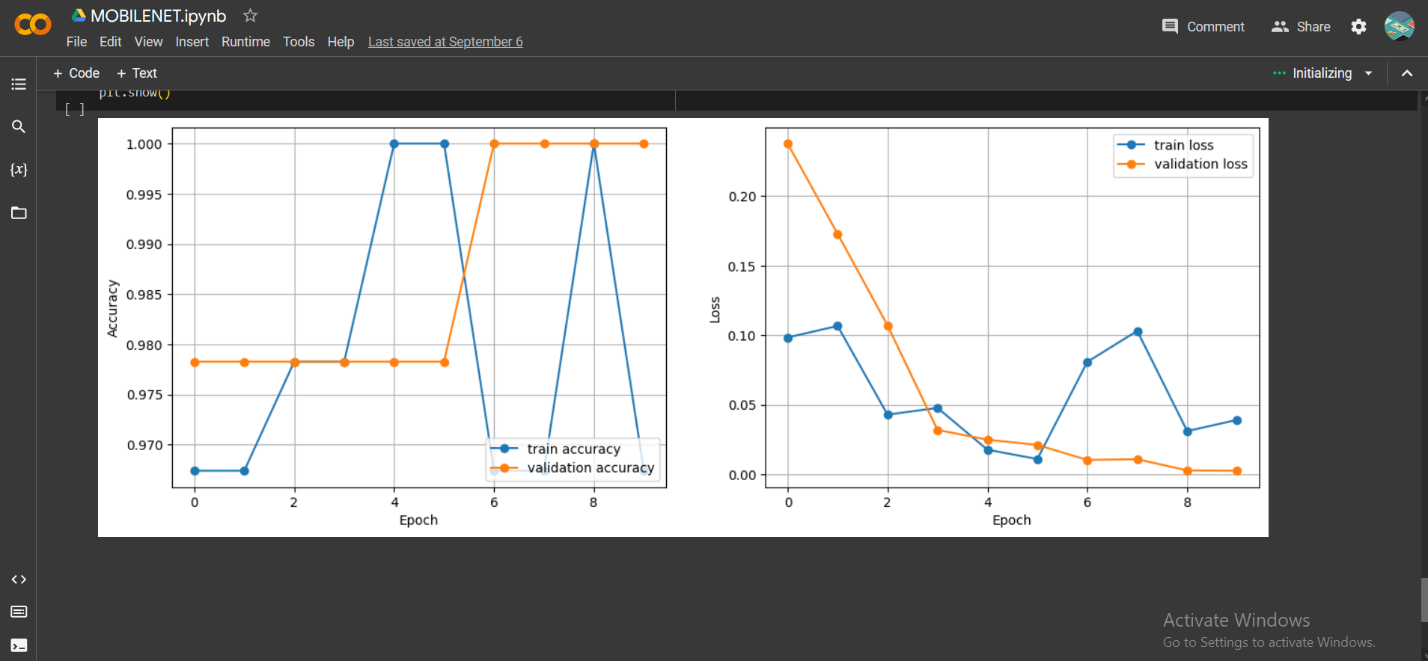
The training set is used to train the model while the validation set is only used to evaluate the model performance and test is set for the test's performance. For training, test and validation accuracy using matplotlib we got a few different graphs for each model. All the plotted graphs are given below-



**Fig: Training and validation loss of mobilenet model**



**Fig: Training and validation loss(Resnet model)Fake and Real Dataset**

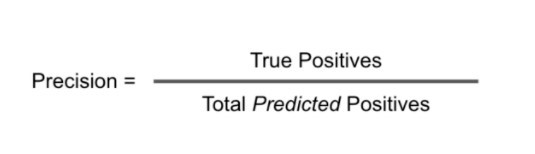
**Fig: Training and validation loss (Mobilenet Model)Fake and Real Dataset**

In this research, we trained Build in model, customize model and got a different kind of test accuracy from our each dataset. In the table listed all the testing accuracy achieved by our one model. From Mobile net fake dataset test accuracy 75.00%, from Real dataset 97% from Resent all fake and real in avgrage 98.00%and 75% from Alexnet . Among all dataset, we got the best accuracy from Resnet Model dataset and it is around 98%

**Table (5): Test Accuracy rate from trained datasets with the CNN model**

|  |  |
| --- | --- |
| **Datasets** | **Test Accuracy Rate** |
| Mobilenet Model Fake Dataset | 75.00% |
| Mobilenet Model Real Dataset | 97.00% |
| Resnet Model Real &Fake Dataset | 98.00% |
| Alexnet Model Real &Fake Dataset | 75.00% |

Evaluating our model performance, we used the precision rate from all dataset. Precision means the ratio of generated result from a system that accurately predicts positive observation (True Positive) to the system divided by total predict positive observation both correct(True Positive) and incorrect (False Positive).To calculate the precision rate, we generated a confusion matrix after training each dataset. To calculate the precision rate, we used the given formula is given in figure.



**Fig: Equation of Precision rate calculation**

The Mobilenet and Alexnet Models both achieved a perfect precision rate of 1.0 on Real and Fake datasets. Additionally, the Resnet Model scored a remarkable 1.0000, showcasing its robustness in distinguishing real from fake data. These high precision rates highlight the effectiveness of these models for various applications.

**Table(6):Precision rate from trained datasets with the CNN model**

|  |  |
| --- | --- |
| **Datasets** | **Precision Rate** |
| Mobilenet Model Fake Dataset | 1.0 |
| Mobilenet Model Real Dataset | 1.0 |
| Resnet Model Real &Fake Dataset | 1.0000 |
| Alexnet Model Real &Fake Dataset | 1.0 |

**Table(6):Precision rate from trained datasets with the CNN model**

F1-Scores for various datasets and models show their precision-recall balance. Mobilenet: perfect 1.0 on Fake and Real. Alexnet: flawless 1.0 on combined Real and Fake. Resnet: strong 0.9773 on Real and Fake. These scores demonstrate model effectiveness across diverse tasks with high accuracy.

**Table (7): F1-score from trained datasets with the CNN model**

|  |  |
| --- | --- |
| **Datasets** | **F1-Score** |
| Mobilenet Model Fake Dataset | 1.0 |
| Mobilenet Model Real Dataset | 1.0 |
| Resnet Model Real &Fake Dataset | 0.9773 |
| Alexnet Model Real &Fake Dataset | 1.0 |

Error rates for various datasets and models indicate incorrect predictions. In this case, Mobilenet, Resnet, and Alexnet all had error rates of 1.0 on their datasets, making no correct classifications. These high error rates suggest a need for model optimization or reevaluation to improve accuracy and reliability in data classification.

**Table(8):Error rate from trained datasets with the CNN model**

|  |  |
| --- | --- |
| **Datasets** | **Error Rate** |
| Mobilenet Model Fake Dataset | 1.0 |
| Mobilenet Model Real Dataset | 1.0 |
| Resnet Model Real &Fake Dataset | 1.0000 |
| Alexnet Model Real &Fake Dataset | 1.0 |

**4.6 Comparison with Previous Research Results:**

The test accuracy is the first thing we consider when evaluating any form of model. Test accuracy refers to how well a model can categorize or predict. The optimal model for prediction and classification will have a higher accuracy. The quantity and quality of the test images have a significant impact on test accuracy. Table (X) shows that for the Bangladeshi Currency dataset that was taken from the Kaggle dataset, our enhanced CNN model had the greatest Test accuracy. With the use of a data augmentation technique and modifications to the CNN layer, our model had the greatest test accuracy rate (96%). All test accuracy figures are provided in Table (9), which compares them to other earlier methods.

**Table(9): Comparison of test accuracy with previous method**

|  |  |
| --- | --- |
| **Method Name** | **Test Accuracy** |
| Improved CNN model | 96% |
| ResNet101 & ResNet50v2 | 91.2% |
| Convolutional encoder networks | 86.78% |

We used the overall dataset's precision rate to assess the efficacy of our model. Precision refers to the ratio of a system's generated results that correctly predict correct image observation to the system divided by all correctly predict both correct and incorrect observation. We attained a precision rate of.96 with our model table(10), the greatest rate among other models.

**Table(10): Comparison of Precision with previous method**

|  |  |
| --- | --- |
| **Method Name** | **Precision Rate** |
| 1. Improved CNN model | 0.96 |
| 2.Convolutional encoder networks | 0.91 |
| 3.CNN's Improved convolution neural networkINAR-SSD [38] | 0.788 |

**Table (11): Comparison of Recall rate with previous method**

|  |  |
| --- | --- |
| **Method Name** | **Recall Rate** |
| 1.Improved CNN model | 0.96 |
| 2.CNN’s Improved convolutional neural networkINAR-SSD | 0.91 |

The ratio of findings that correctly forecast positive observations (True Positive) to all observations in the actual malignant class (Actual Positive) is known as recall. The highest recall rate is always valued for the best classification model. Recall rate is mostly affected by model quality and image quality. This model will yield a greater recall rate and accurately predict and classify images if the training model and all the training images are in good shape. We received our model. The confusion matrix recall rate was 96, which is an improvement over the prior study.

In addition, we had a 0.05 error rate according to our model. Classifying fake from original from an input image takes an average of 457 milliseconds to predict a single image. The Bangladeshi Currency dataset gave us the greatest overall result out of all the datasets, and we anticipate that with further development and improvement, our model will become more accurate.

**4.5 Conclusion**

For the first time, we implemented our model without data augmentation in each trial, using a new type of step to improve the model performance across all datasets. This resulted in a low accuracy rate, a significant validation loss, and poor testing accuracy. We employed data augmentation and increased the number of photos to address the overfitting issue. Using that, we significantly outperformed our previous effort. But it was in no way satisfactory. For the experiment, we then tried to fine-tune our parameter. Google Colab's runtime environment would break if we chose a high epoch. To do that, we changed the learning rate, dropout rate, and optimizer as well as the epochs in accordance with Colab. We were able to increase the accuracy of our model by over 20% through applying this method of modeling. Then, in order to improve model performance and accuracy, we made our model network deep. We got a good outcome because of that. In the future, we'll try to use cross-validation approaches to increase the performance of our model.

**Chapter 5: Conclusion and Future Work**

**5.1** **Introduction**:

Counterfeiting of currency notes poses a significant threat to financial systems and consumer trust worldwide. To combat this issue, the development of robust fake currency detection systems is crucial. In this context, we present an implementation of a fake currency detection system that leverages state-of-the-art techniques in deep learning and computer vision. Our system's foundation lies in meticulous data preprocessing, ensuring that our model receives data in the optimal format required by the MobileNet architecture. Leveraging transfer learning, we build upon a pre-trained MobileNet model, fine-tuning it for the specific task of currency note classification. This approach not only enhances model performance but also reduces training time significantly comprehensive evaluation metrics, including precision, F1-score, and accuracy, are employed to provide a holistic assessment of the model's effectiveness. Visualizing the confusion matrix aids in identifying areas of model weakness and potential for improvement. Furthermore, we've developed an image preprocessing function and a user-friendly interface, enhancing the practicality and accessibility of our solution for end-users in real-world applications. In this dynamic landscape of counterfeit currency detection, our system represents a solid starting point. However, there is ample potential for further growth and innovation in addressing the challenges posed by counterfeit currency. This implementation serves as a foundation upon which future work can build, ultimately contributing to more secure financial systems and safeguarding consumer trust.

**5.2 Contribution of the Research:**

Our code implementation for fake currency detection offers several key contributions to the field. Firstly, we prioritize data preprocessing to ensure that our model receives data in the optimal format required by the MobileNet architecture, a crucial step for effective model training. Leveraging transfer learning, we build upon a pre-trained MobileNet model, harnessing the wealth of knowledge acquired from ImageNet and fine-tuning it for our specific currency note classification task. This strategic approach not only boosts model performance but also significantly reduces training time. We employ a range of comprehensive evaluation metrics, including precision, F1-score, and accuracy, to provide a holistic assessment of our model's effectiveness, addressing the precision-recall balance essential in currency note detection. The visualization of the confusion matrix aids in pinpointing areas of model weakness and potential areas for improvement. Furthermore, we've created an image preprocessing function and a user-friendly interface, enhancing the model's practicality and accessibility for end-users in real-world scenarios. In summary, our implementation empowers the field of fake currency detection by offering a robust, user-friendly, and effective solution that combines state-of-the-art techniques with accessibility.

**5.3 Future Work:**

Moving forward, there are several avenues for future work in fake currency detection. Firstly, we can augment our dataset with more diverse images and apply advanced data augmentation techniques. Exploring advanced deep learning architectures, ensemble learning methods, and object detection techniques could lead to even higher accuracy and more versatile applications. Real-time detection capabilities, integration with hardware devices, and deployment in banking and retail sectors represent exciting possibilities. Moreover, we should consider continuous learning to adapt to evolving counterfeit techniques and regulatory compliance to ensure adherence to currency handling standards. Ethical considerations and security measures against adversarial attacks are also vital for building a trustworthy system. Finally, international currency support, scalability, and a feedback loop with users and experts will further enhance the effectiveness and relevance of our fake currency detection system in various real-world scenarios. In the realm of fake currency detection, our system's future work holds the potential for significant advancements. By expanding and diversifying our dataset through advanced data augmentation techniques, we aim to bolster our model's ability to handle a wider array of counterfeit notes. Exploring advanced deep learning architectures, implementing real-time detection capabilities, and delving into object detection for security feature identification are avenues to further elevate the system's accuracy and versatility. Continuous learning mechanisms will allow our system to adapt to evolving counterfeit techniques, while ethical considerations, security measures, and international currency support will ensure its reliability and applicability in various contexts. Moreover, ongoing user interface enhancements, regulatory compliance, and a feedback loop with stakeholders will contribute to making our system more user-friendly and aligned with real-world needs. These future endeavors promise to strengthen our fake currency detection system's effectiveness and practicality, reinforcing its role in safeguarding financial integrity and trust.

**5.4 Conclusion**:

In this implementation of a fake currency detection system, we have achieved several notable milestones. By meticulously preprocessing our dataset and harnessing the power of transfer learning through MobileNet, we've built a robust model capable of distinguishing between fake and real currency notes. The incorporation of comprehensive evaluation metrics, including precision, F1-score, and accuracy, has provided a thorough assessment of our model's performance, crucial for ensuring both precision and recall in currency note detection. Visualizing the confusion matrix has enabled us to identify areas for potential improvement. Moreover, we've created an image preprocessing function and a user-friendly interface, making our solution accessible and practical for end-users in real-world applications. However, the journey doesn't end here. Future work should focus on expanding the dataset, exploring advanced models, implementing real-time detection, and ensuring ethical considerations and security measures to maintain trustworthiness. Our system has laid a solid foundation, but there is ample room for growth and enhancement in the exciting field of fake currency detection.

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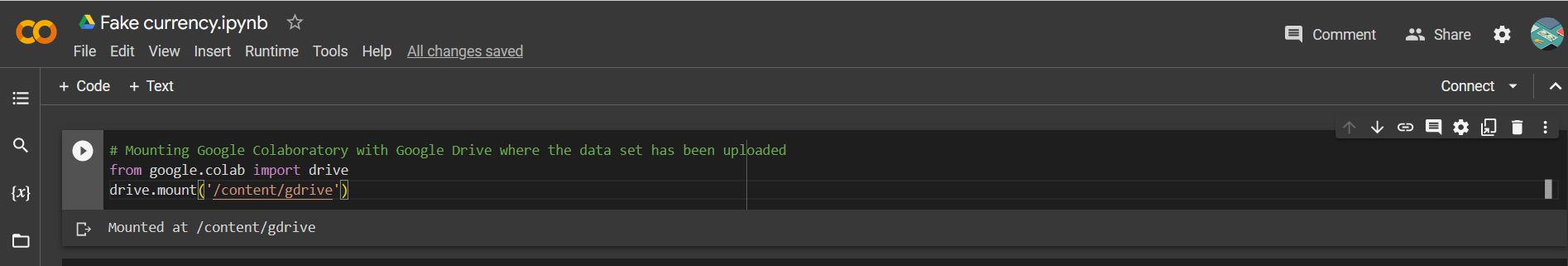
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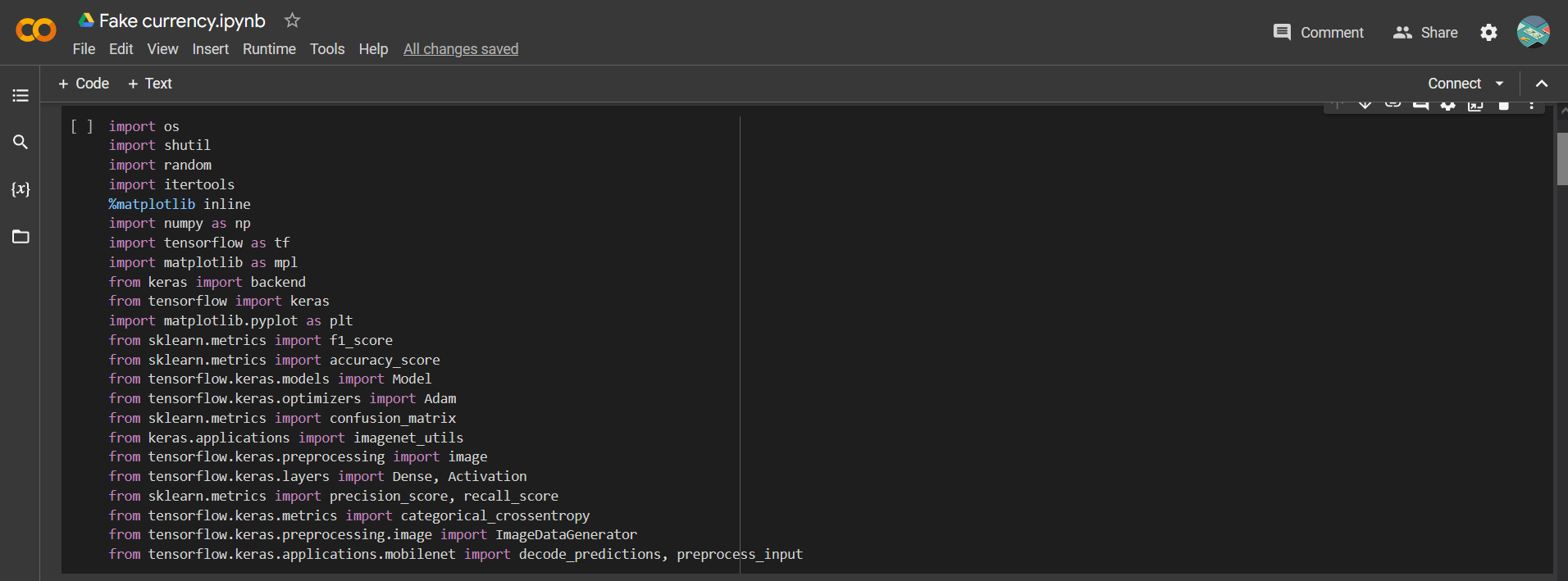
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**Appendix A**

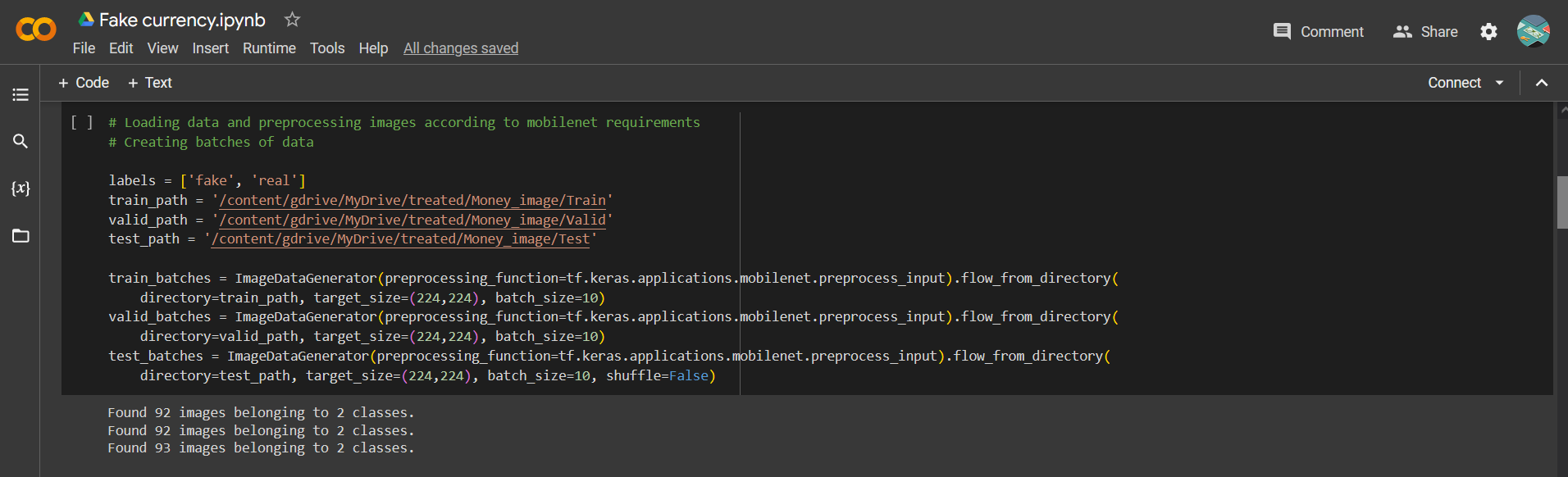
**\*\*Mounting with Google drive\*\***

****

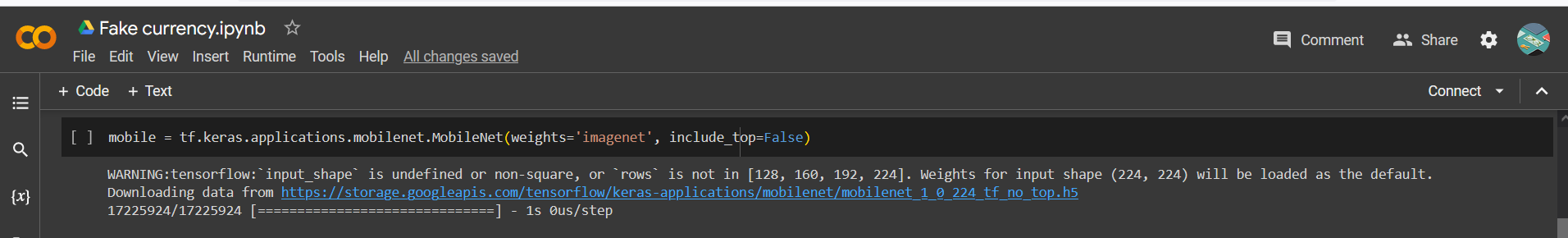
**\*\*Importing Necessary Libraries\*\***

****

**\*\*Loading dataset devided into Train, Valid and Test\*\***

****

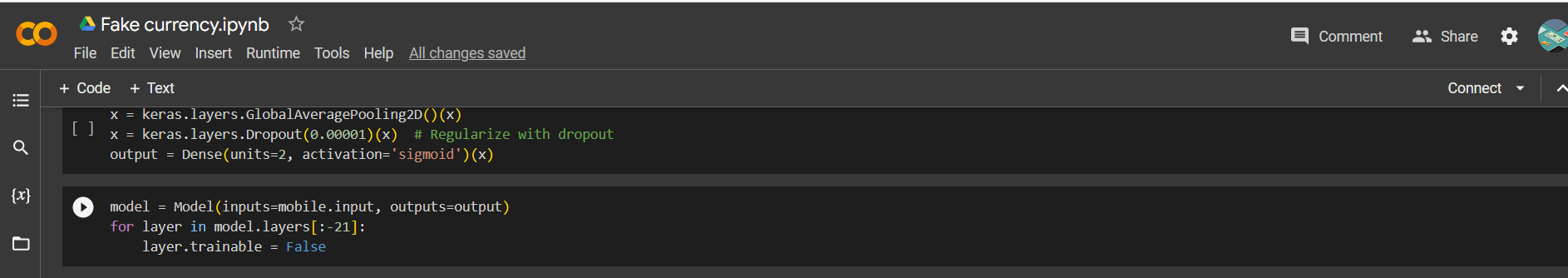
**\*\*Including Fake currency Model\*\***

****

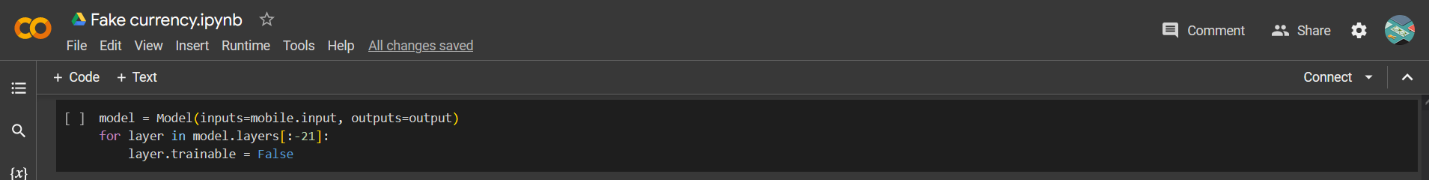
**\*\*Defining which layers will be trained\*\***

****

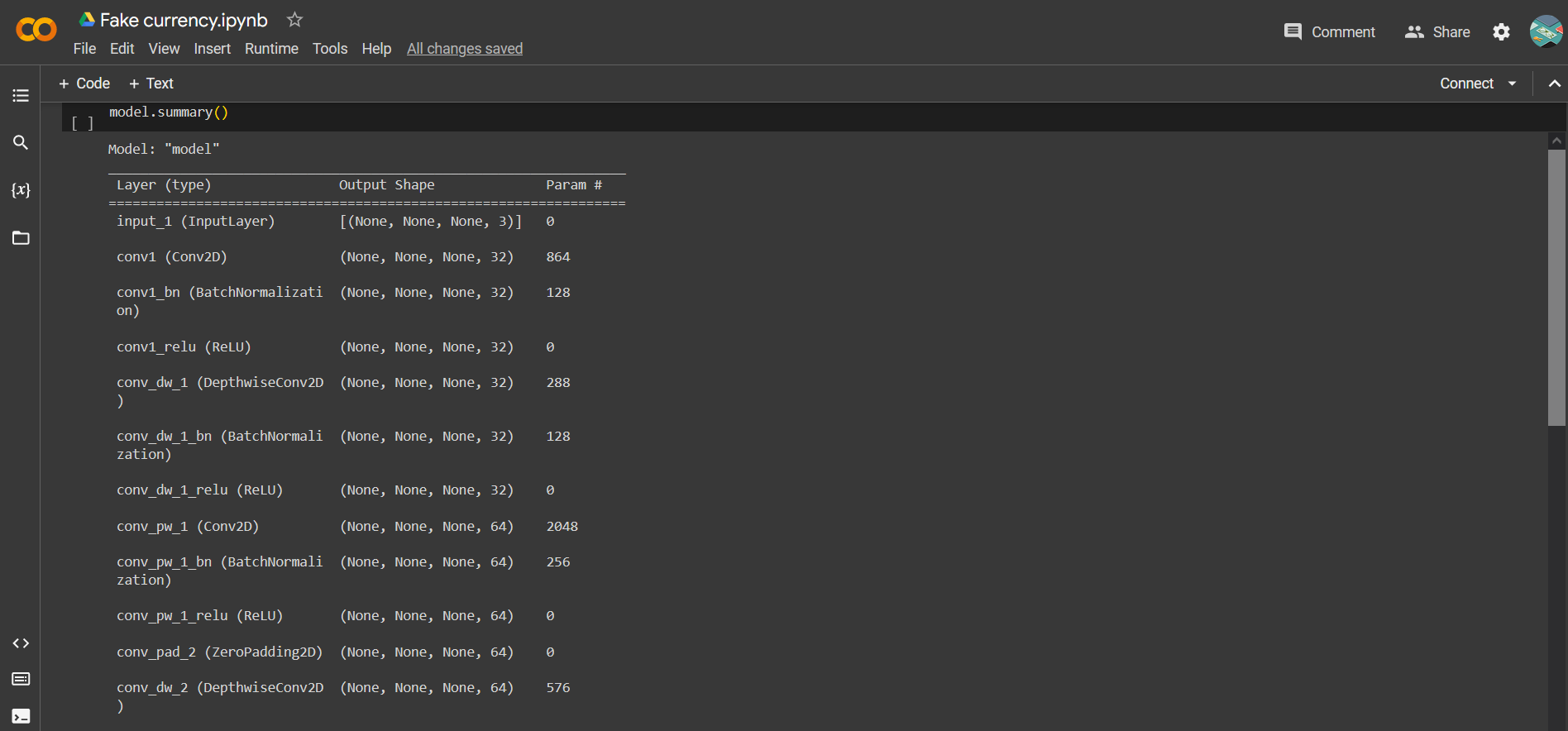
**\*\*Implementing Pooling, Regularization, Dense layer and Activation function\*\***

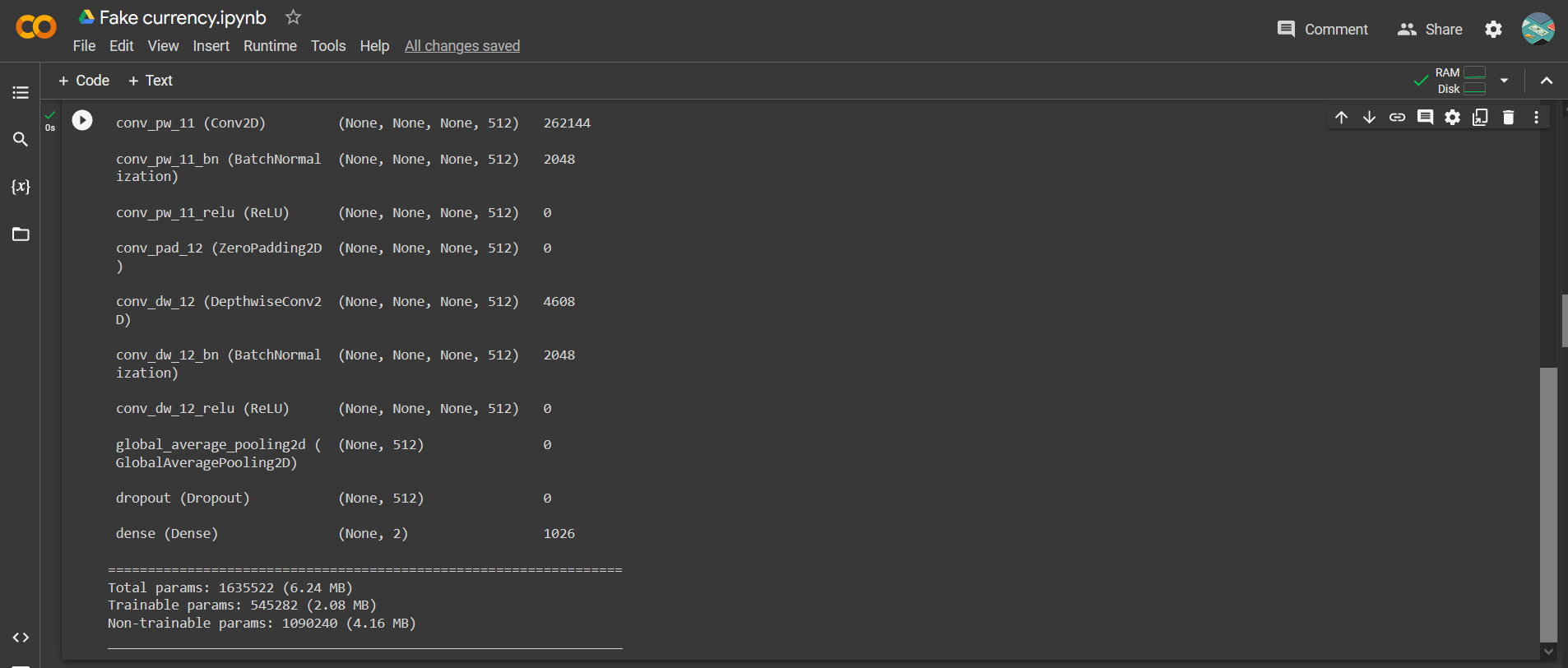
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**\*\*Defining the model\*\***

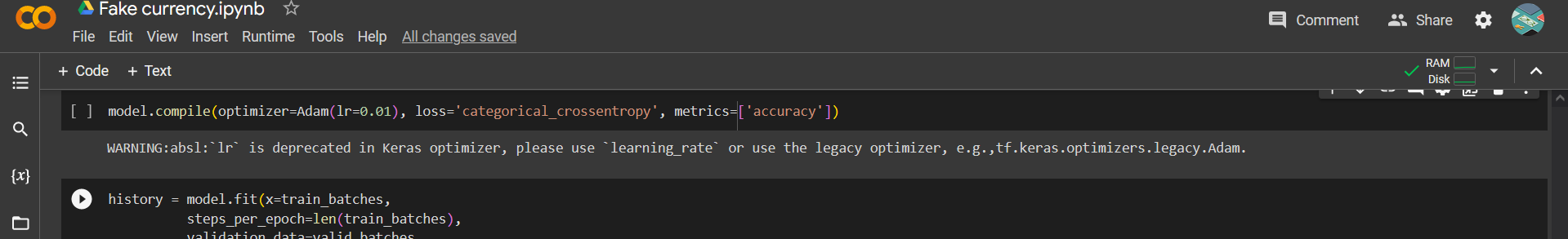
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**\*\*The Main Model\*\***

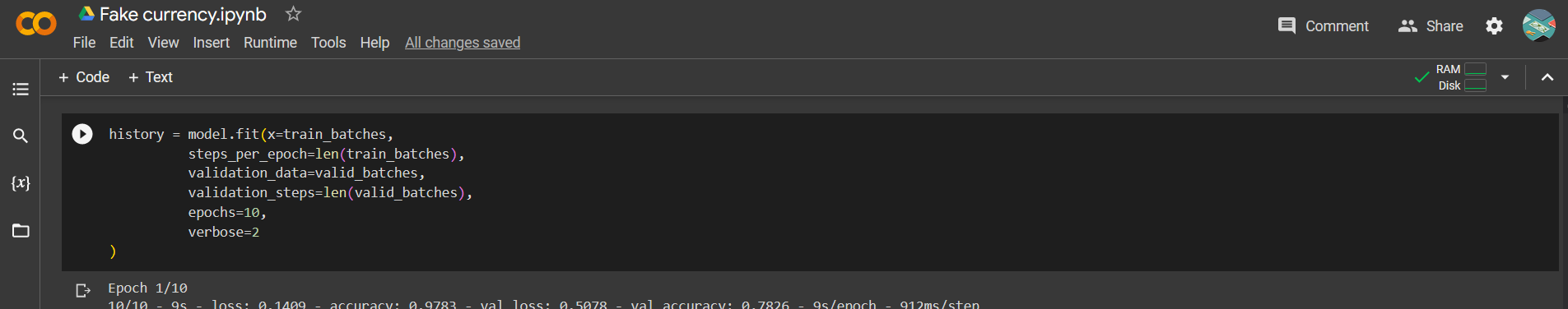
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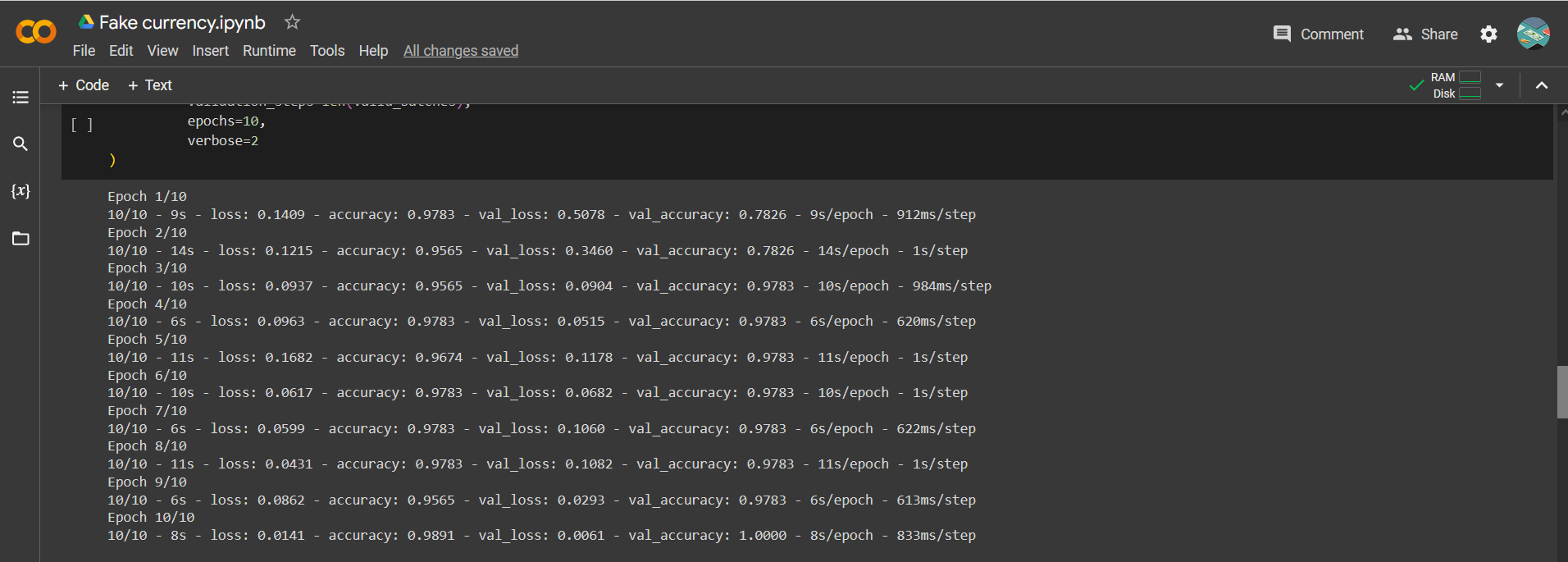
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**\*\*Compiling the model\*\***

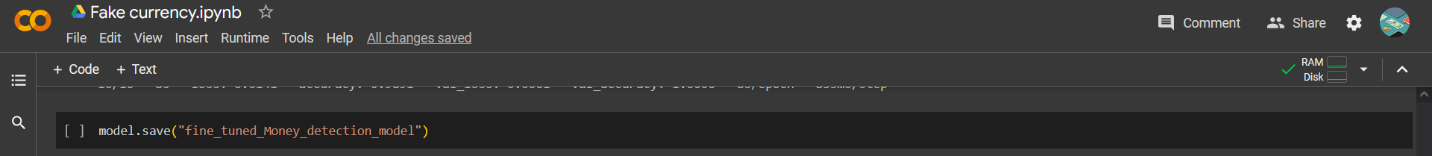
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**\*\*Model Fitting\*\***

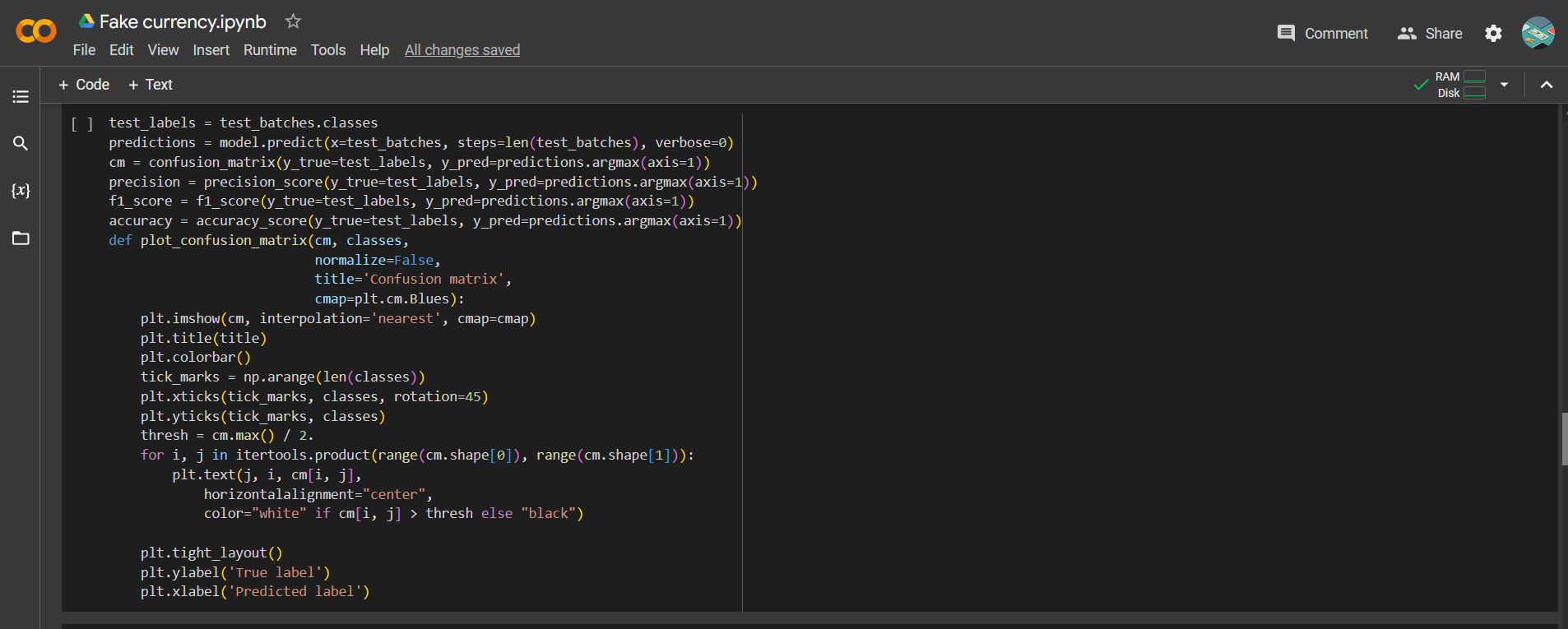
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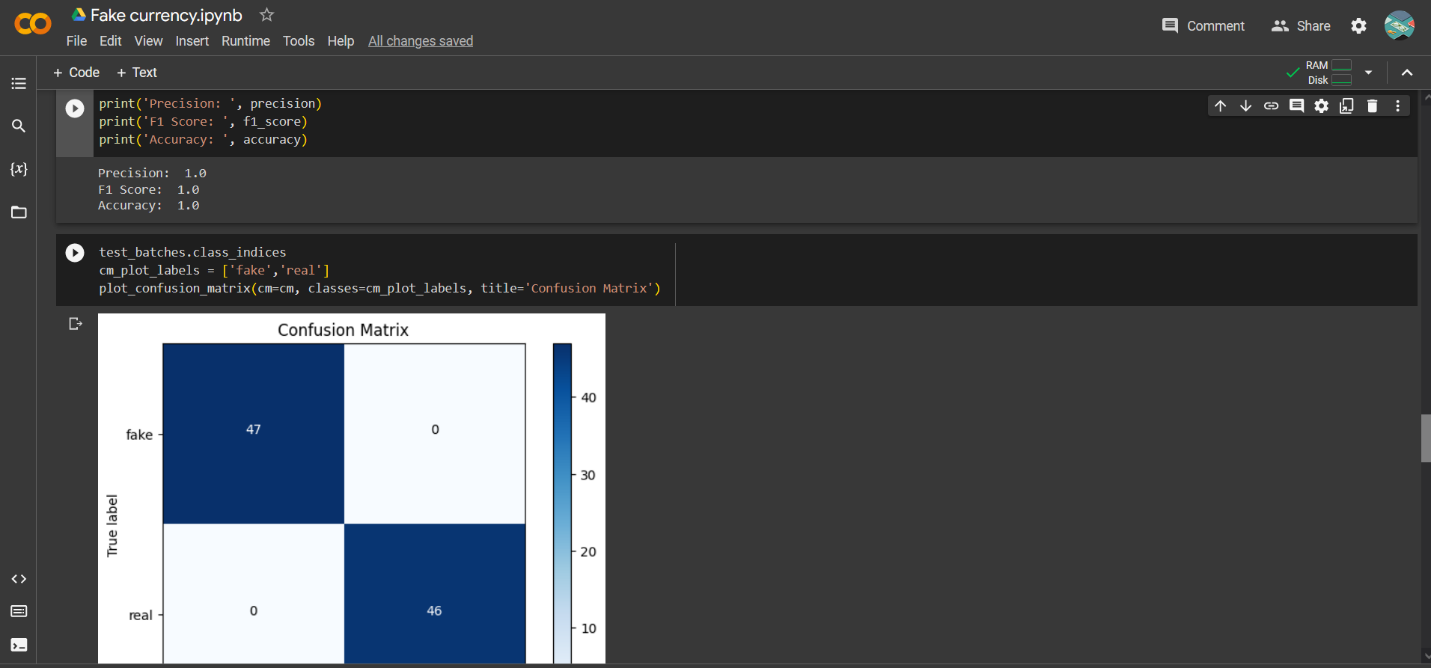
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**\*\*Saving the model for later use\*\***

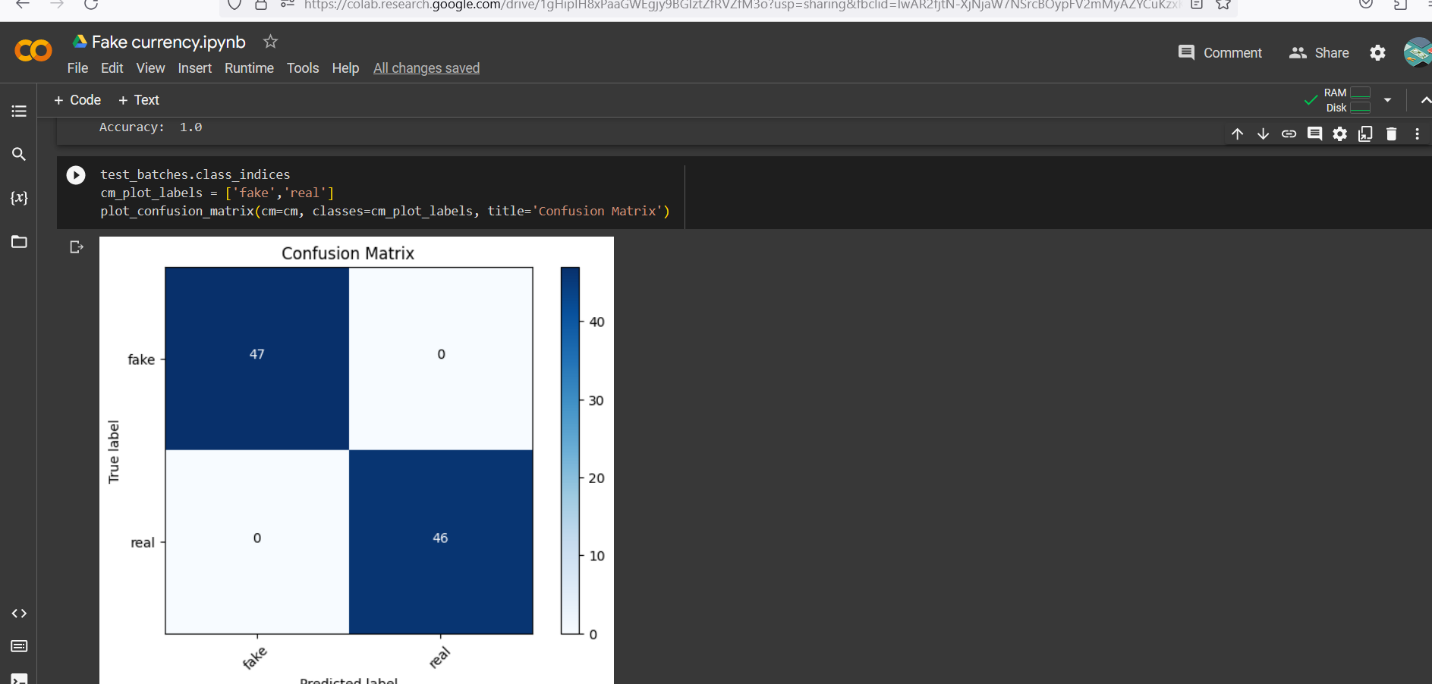
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**\*\*Defining labels\*\***

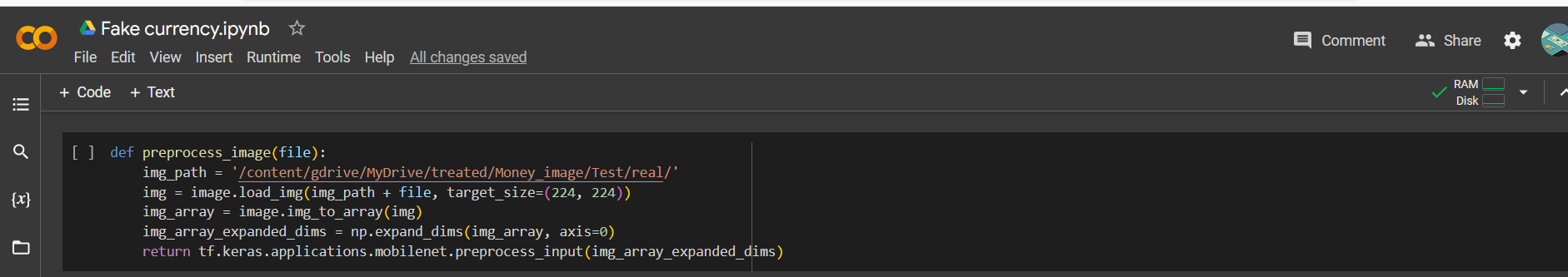
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**\*\*Showing Precision, F1 Score and Accuracy\*\***

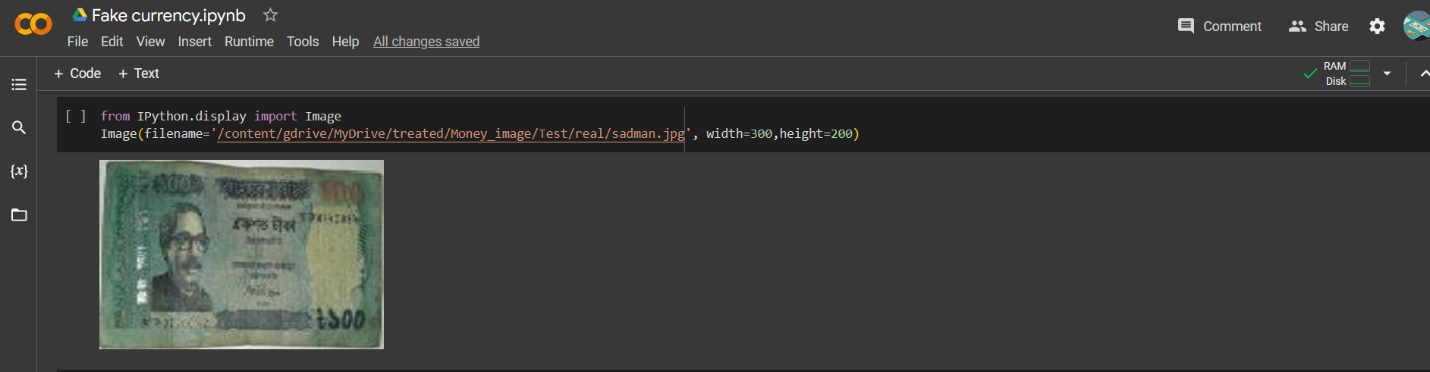
**\*\*Plotting Confusion Matrix\*\***

****

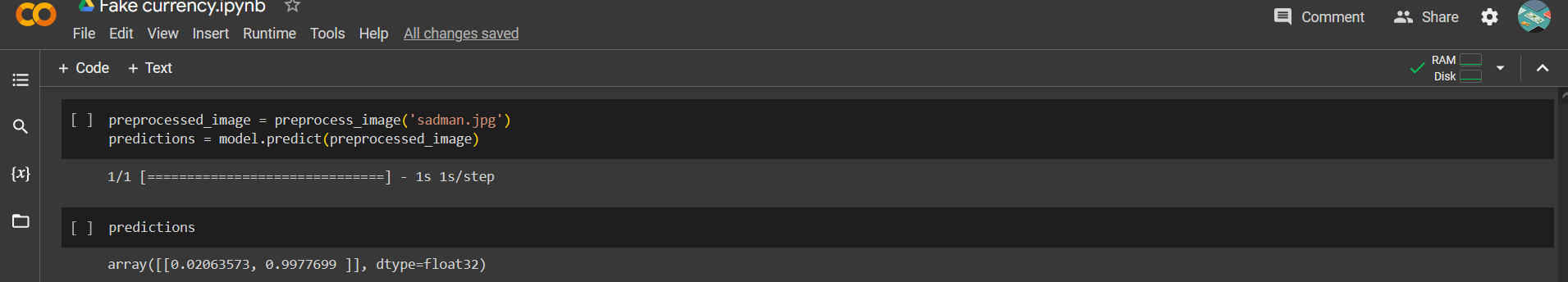
**\*\*Preprocessing Images\*\***

****

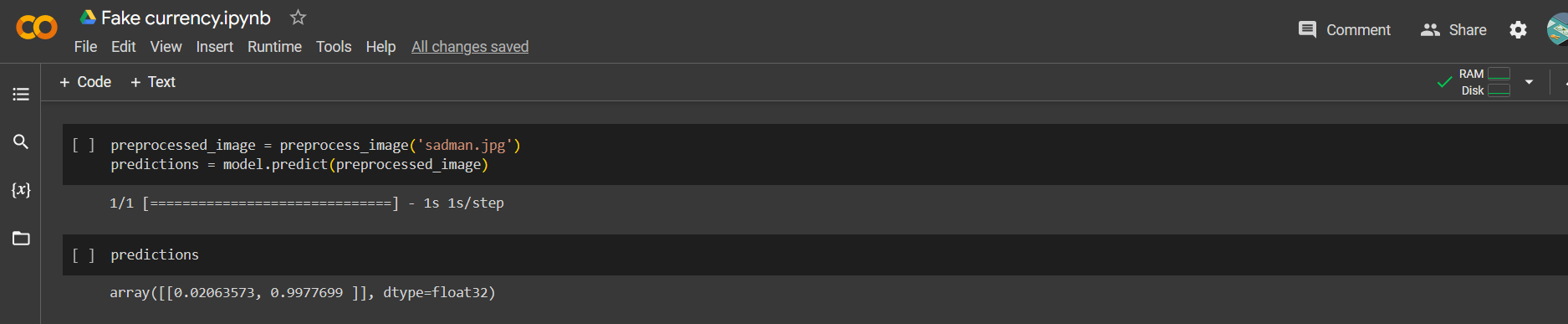
**\*\*Showing the image that we want to test\*\***

****

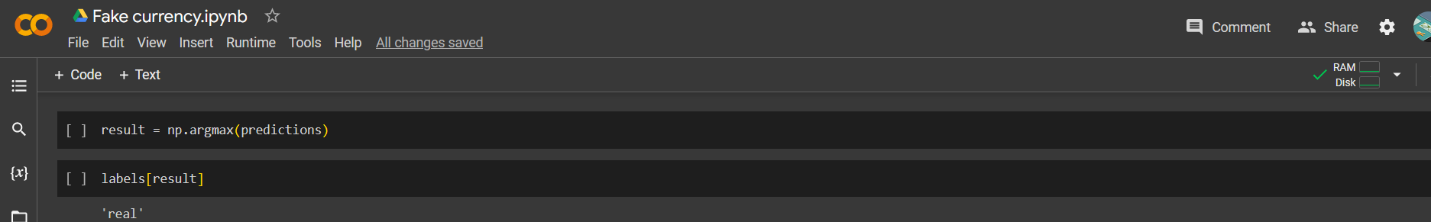
**\*\*Loading the image for prediction\*\***

****

**\*\*Predicting the image\*\***

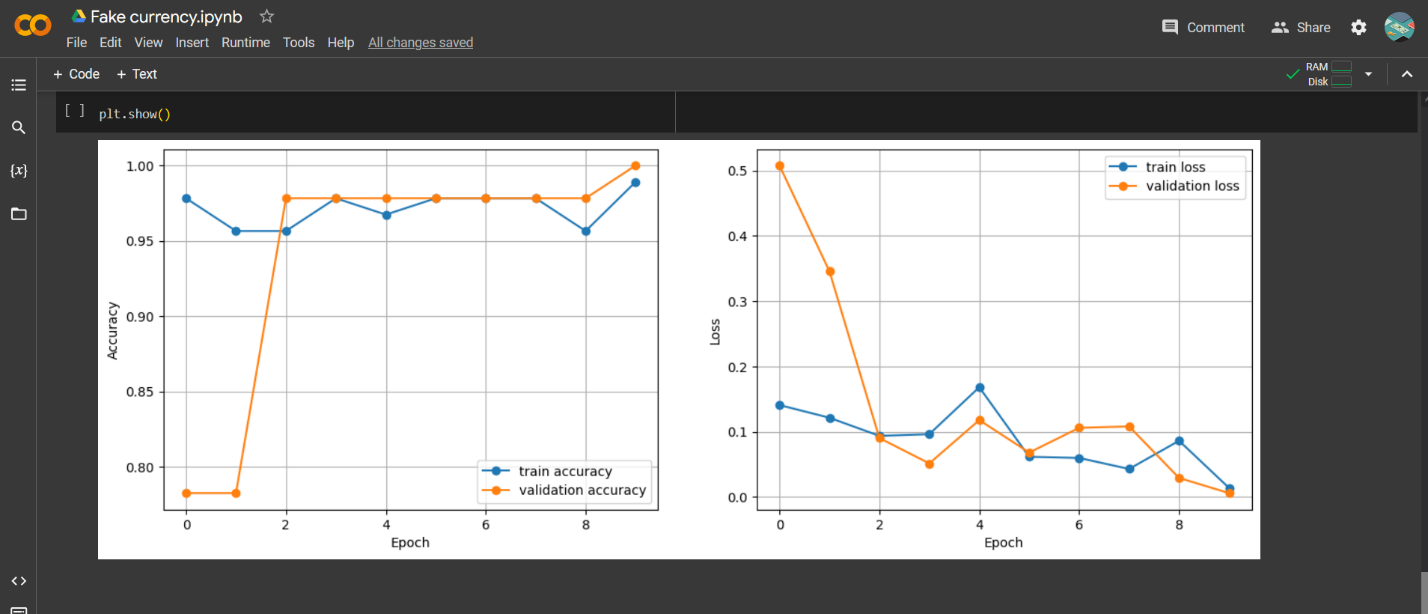
****

**\*\*Predicted result\*\***

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**\*\*Plotting Accuracy and Loss graph on Training and Validation Data\*\***

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