Deep Learning Approach to Detect Counterfeit Medicine in Bangladesh

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This Thesis report has been submitted in fulfillment of the requirements for the Degree of Bachelor of Science in Software Engineering

APPROVAL

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This thesis titled on **"Deep Learning Approach to Detect Counterfeit Medicine in Bangladesh"**, submitted by **Mst. Sanjana Mahin Shejuty (ID: 202-35-3116)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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Declaration

I announce that I am rendering this study document under Ms. Fatama Binta Rafik, Lecturer (Senior Scale) , Department of Software Engineering, Daffodil International University. I therefore, state that this work or any portion of it was proposed here therefore for Bachelor's degree or any graduation.

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Abstract

In Bangladesh, counterfeit medications pose a serious threat to public health since they reduce treatment ability and erode public confidence in the medical establishment. This thesis focuses on creating a deep learning-based system for detecting counterfeit medications with the goal of improving the precision and dependability of detecting counterfeit pharmaceutical items. Using a deep learning framework, the study processes and analyzes these photographs with the goal of identifying authentic products from counterfeit ones by comparing minute variations in logos of pharmaceutical companies in Bangladesh. These visual cues are essential for spotting fakes since they frequently have dangerous or inaccurate components. This study's foundation is a specially-assembled dataset of 1,543 pictures, divided between 879 genuine and 664 fake logos. The photos serve as a varied base for training and testing the detection system. They are taken from official pharmaceutical channels and enforcement seizures. Carefully dividing the dataset into separate sets for testing, validation, and training allows for a thorough assessment of the system's performance on untested data. The detection system's performance is assessed using measures like mean Average Precision (mAP), F1-score, accuracy, precision, and recall. These measures measure the system's efficacy in effectively identifying counterfeit products while reducing false positives, which gives regulatory and health organizations dependable support. The study's findings demonstrate the potential benefits of using cutting-edge data analysis methods to important public health applications. The suggested approach can play a major role in protecting public health by effectively recognizing fake medications. In addition, this study establishes the foundation for future developments in the use of technology to address health-related issues, and it may also broaden its approach to other industries where the use of fake goods is problematic.

Table of Contents

List of Figure

Chapter 01

Introduction

1.1 Introduction

In a developing country like Bangladesh, counterfeit medicines pose a significant threat to public health and safety. These fake medications often contain incorrect or harmful ingredients, leading to adverse health effects and undermining trust in healthcare systems. Detecting counterfeit medicines is challenging due to the sophisticated techniques used by counterfeiters to mimic genuine products. This thesis addresses this issue by leveraging advanced deep learning techniques to develop robust models capable of accurately identifying counterfeit medicines.

The primary objective of this research is to utilize modern deep learning architectures to analyze one of the key features of medicine packaging which is logos of pharmaceutical companies to distinguish between genuine and fake products. By employing pre-trained models like VGG-16 and ResNet50 and fine-tuning them with custom layers, this study aims to create an effective and reliable detection system. The dataset, comprising images of both real and counterfeit medicines, is meticulously prepared and augmented to enhance the models' training and generalization capabilities.

This thesis not only focuses on the technical aspects of model development and training but also evaluates the practical application potential of these models. Performance metrics such as accuracy, precision, recall, F1-score, and mean Average Precision (mAP) are used to assess the models' effectiveness. The findings highlight the strengths and limitations of each model, providing insights into their suitability for real-world deployment.

Through this research, we aim to contribute to the fight against counterfeit medicines by providing a powerful tool for detection, ultimately improving public health outcomes and ensuring the safety and efficacy of pharmaceutical products. This thesis sets the stage for further advancements in counterfeit detection, exploring new methodologies and expanding the scope of application to other domains where counterfeit products are prevalent.

1.2 Background

Counterfeit medicines are a significant global issue, particularly in low and middle-income countries, where up to 30% of medicines may be fake. These counterfeit drugs often contain incorrect or harmful ingredients, leading to treatment failures and increased health risks. In Bangladesh, the problem is exacerbated by weak regulatory enforcement and the presence of informal markets, putting millions at risk.

Traditional counterfeit detection methods, such as visual inspection and laboratory analysis, are often inadequate due to the sophistication of modern counterfeiters and limited resources. These methods are also time-consuming and require specialized skills and equipment.

Given these challenges, there is increasing interest in using advanced technologies like deep learning to improve counterfeit detection. Deep learning models can analyze images and recognize subtle differences in logos, packaging and other features indicative of counterfeit products.

This thesis explores the use of state-of-the-art deep learning architectures to develop a robust system for detecting counterfeit medicines in Bangladesh. By fine-tuning these pre-trained models with custom layers, the research aims to create a reliable tool for identifying counterfeit medicines based on key visual features.

1.3 Motivation

The pervasive issue of counterfeit medicines poses a dire threat to public health and safety, particularly in developing countries like Bangladesh. Counterfeit drugs, often containing incorrect or harmful ingredients, lead to ineffective treatments, increased morbidity, and even mortality. The widespread presence of these counterfeit medicines erodes trust in healthcare systems and endangers the lives of millions. Despite ongoing efforts to combat this problem, traditional methods of detection have proven inadequate, primarily due to the sophistication of counterfeiters and limited resources for thorough inspections.

In light of these challenges, there is an urgent need for innovative and effective solutions to detect counterfeit medicines. Advances in deep learning technology offer a promising avenue for developing such solutions. Deep learning models excel in image analysis and pattern recognition,

making them well-suited for identifying subtle differences in medicine packaging that indicate counterfeit products. By leveraging these advanced technologies, we can develop robust, scalable, and accessible tools for counterfeit detection.

The motivation for this thesis stems from the critical need to address the limitations of current detection methods and provide a reliable solution to combat counterfeit medicines. By focusing on the application of state-of-the-art deep learning architectures, this research aims to significantly enhance the ability to identify counterfeit medicines, thereby protecting public health and restoring trust in the healthcare system. The potential impact of this work extends beyond Bangladesh, offering a framework that can be adapted and applied to other regions facing similar challenges.

Ultimately, this thesis seeks to contribute to the global fight against counterfeit medicines by harnessing the power of deep learning to create a practical, efficient, and effective detection system. The successful implementation of this research could lead to widespread adoption of advanced counterfeit detection technologies, ensuring safer and more reliable access to essential medicines for all.

1.4 Problem Statement

Counterfeit medicines pose a serious threat to public health in Bangladesh, leading to ineffective treatments and increased health risks. Traditional detection methods are often inadequate due to sophisticated counterfeiting techniques and limited resources. Despite ongoing efforts, the prevalence of counterfeit medicines continues to rise, undermining trust in healthcare systems.

There is an urgent need for more effective, scalable, and accessible detection methods. This thesis aims to address this critical issue by leveraging advanced deep learning techniques to develop models capable of accurately distinguishing between genuine and counterfeit medicines based on logos of pharmaceutical companies. By creating a reliable tool for counterfeit detection, this research seeks to enhance public health and safety.

1.5 Research Gap

Despite ongoing efforts to combat counterfeit medicines, significant gaps remain in the detection methods currently employed. Traditional approaches, such as visual inspections and laboratory analyses, are often inadequate due to their resource-intensive nature and inability to effectively identify sophisticated counterfeiting techniques. These methods are also time-consuming and require specialized skills and equipment, making them impractical for widespread use in regions with limited resources.

Furthermore, while advances in technology have been applied to various aspects of healthcare, the use of deep learning techniques specifically for counterfeit medicine detection is still underexplored.

This thesis aims to address these research gaps by developing and fine-tuning deep learning models capable of accurately distinguishing between genuine and counterfeit medicines. By utilizing advanced architectures of deep learning this study seeks to create a scalable, efficient, and accessible detection system. This research not only enhances the existing methodologies but also sets the stage for future advancements in counterfeit detection technologies.

1.5 Research Questions

- How can deep learning models be effectively utilized to detect counterfeit medicines based on logos of the pharmaceutical companies?
- What are the most effective data augmentation and preprocessing techniques for enhancing the accuracy and robustness of deep learning models in counterfeit medicine detection?
- How can a diverse dataset for medicines be collected and annotated effectively to train the system?

1.6 Research Objectives

To explore and implement effective data augmentation and preprocessing techniques that improve the models' ability to generalize and perform accurately in various conditions. Need to

comprehensively evaluate the performance of the developed models using metrics such as accuracy, precision, recall, F1-score, and mAP, and to compare their effectiveness in counterfeit medicine detection. To design a scalable and accessible counterfeit medicine detection system that can be deployed in real-world scenarios, enhancing public health and safety.

1.7 Research Scope

The scope of this thesis encompasses the development, fine-tuning, and evaluation of deep learning models for counterfeit medicine detection. The research focuses on leveraging pre-trained architectures of deep learning incorporating custom layers and effective data augmentation techniques. The dataset includes images of genuine and counterfeit medicines, with annotations for logos, color regions, and expiration dates. The study aims to create a robust detection system that can be deployed in various settings, particularly in resource-limited regions like Bangladesh. The scope also includes a comparative analysis of model performance and the exploration of practical applications for enhancing public health and safety.

Chapter 02

Literature Review

2.1 Introduction

In our investigation of the "Literature Review" category, we meticulously examined a broad array of sources, including prior publications, research papers, conference proceedings, books, articles, and other academic resources. Despite the challenges posed by the limited availability of directly relevant papers on counterfeit medicine detection, we focused on critical topics related to the application of deep learning in image analysis and counterfeit detection. We adopted a comprehensive approach to reviewing the existing body of knowledge in these areas, recognizing the scarcity of directly pertinent materials.

We carefully analyzed previous studies to extract valuable insights and techniques that could form the foundation of our own research. By distilling the key ideas from these past publications, we aimed to synthesize these findings with our research objectives. This synthesis sought to bridge the gaps in the current body of knowledge and identify areas where our study could make a significant impact. Our thorough literature review allowed us to connect disparate perspectives and close the gap between previous research efforts and the specific goals of our study.

In essence, the process of reviewing the literature served as a guide to navigate the intellectual landscape of deep learning applications in counterfeit medicine detection. By exploring the wealth of available information, we gained a deeper understanding of the subject matter and enhanced our ability to evaluate and interpret previous research. This nuanced approach ensures that our contributions are well-informed, relevant, and poised to advance the body of knowledge in the rapidly evolving field of deep learning and counterfeit detection. By situating our work within the broader academic discourse, we aim to provide meaningful insights that enhance public health and safety through improved counterfeit medicine detection technologies.

2.2 Previous Literature

Barstis et al. developed a paper analytical device (PAD) for identifying low-quality pharmaceutical products using chemical test cards and mobile phone image analysis [1]. Alsallal et al. proposed using an X-ray fluorescence machine to detect fake Tenormin medicine, followed by a machine learning technique [1]. Various advanced technologies like edible tags and hardware such as 'Entrupy' have been proposed for counterfeit detection, but they may increase medicine prices [1]. Sharma et al. used support vector machine and convolutional neural network models to identify real or fake products with microscopy images [1]. Barstis et al. invented a paper analytical device (PAD) that can identify lowquality pharmaceutical products [3]. The main component of the device is a chemical test card that has several reagents on it for detecting different kinds of ingredients of the medicine. Putting a suspected medicine on it, then into water, will change the active color barcode present in the card.

Alsallal et al. proposed a method that used an X-ray fluorescence minipal 2 machine to identify if a TenorminR 50 mg medicine is fake or real by analyzing the ingredients and then they proposed a machine learning technique to replace a trained chemist for identifying fake Tenormin [2]. Their method may be used in a hospital environment and not applicable to general customers. There are several approaches proposed that utilized advanced technology such as edible tags attached with every pill [9]. Though these approaches could identify counterfeit medicine with better accuracy they also would increase the price of the medicine. Thus, such technology may not be available in our country in near future.

Several other fake detection approaches based on machine learning have been proposed for identifying products made with leather, fabric, paper, plastic, etc. Sharma et al. developed hardware called “Entrupy” for taking microscopy images of the product [13]. They trained support vector machine (SVM) and convolutional neural network (CNN) with the microscopic image dataset created with their device and achieved better accuracy with the CNN model in identifying a real or fake product. S¸erban et al. used images taken with a mobile phone to train the CNN model to identify real or fake luxury products like Louis Vuitton bags [12].

Prof. Kriti Motwani, Rachel Dsouza, Rhea Dsouza, Janice Jose proposed a technique where deep learning techniques effectively identify counterfeit medicines in India by analyzing packaging details with SSD and Azure OCR. Tough the paper lacks details on deep learning models, dataset specifics, performance metrics, and scalability of the method for detecting counterfeit medicines[3]. BS Thamson, WR Varuna proposed a method where ML algorithms were used to detect counterfeit medicines, with SVM achieving the highest accuracy of 94.5%. Lackings: Lacking's of comparative analysis of each algorithm's performance [5].

Chapter 03

Methodology

3.1 Introduction

This paper proposed a way of training a deep learning model to identify fake medications based in Bangladesh, focusing on logos of various pharmaceutical companies. As a result, our approach to counterfeit drug detection leverages the most advanced deep learning techniques to mitigate these high levels of risk.

The pipeline consists of the following main stages: data preparation, preprocessing, model selection and training, and evaluation. We begin by gathering images of real and fake pharmaceutical companies logos, annotating and augmenting these images. We used various CNNs and object detection models, fine-tuning and optimizing them during training for model selection. The evaluation includes a number of detailed metrics to stabilize outcomes and make them meaningful.

A well-developed and industry-based model is built through these phases. Each step is described separately in its following sections to help Bangladesh rid itself of counterfeit medicine completely.

3.2 Architectural Design

3.2.1 Dataset Description

The dataset used in this research comprises only of the real and fake logo images from multiple Bangladeshi pharmaceutical companies. The collection here tries to capture those small, almost imperceptible differences and discrepancies between the actual logos of a bunch of pharma companies on their boxes and blisters. The dataset to aid training deep

learning models on detection as well classification of the logos at variant scale, size, color will surely assist in detecting counterfeit products successfully under real-time setting.

3.2.2 Dataset Collection

In this thesis, we create the dataset from various real and counterfeit logos of different pharmaceutical companies in Bangladesh. Authentic logos sources from pharmaceutical companies' official resources and verified regulatory databases were gathered. These logos were then illegally sourced from law enforcement seizures, market surveys, and documented case studies of known counterfeit incidents. It provides a broad overview of the current universe of drug products incorporating a wide variety of real and falsified logos. The images were obtained and then digitized for further preprocessing, which occur before model training.

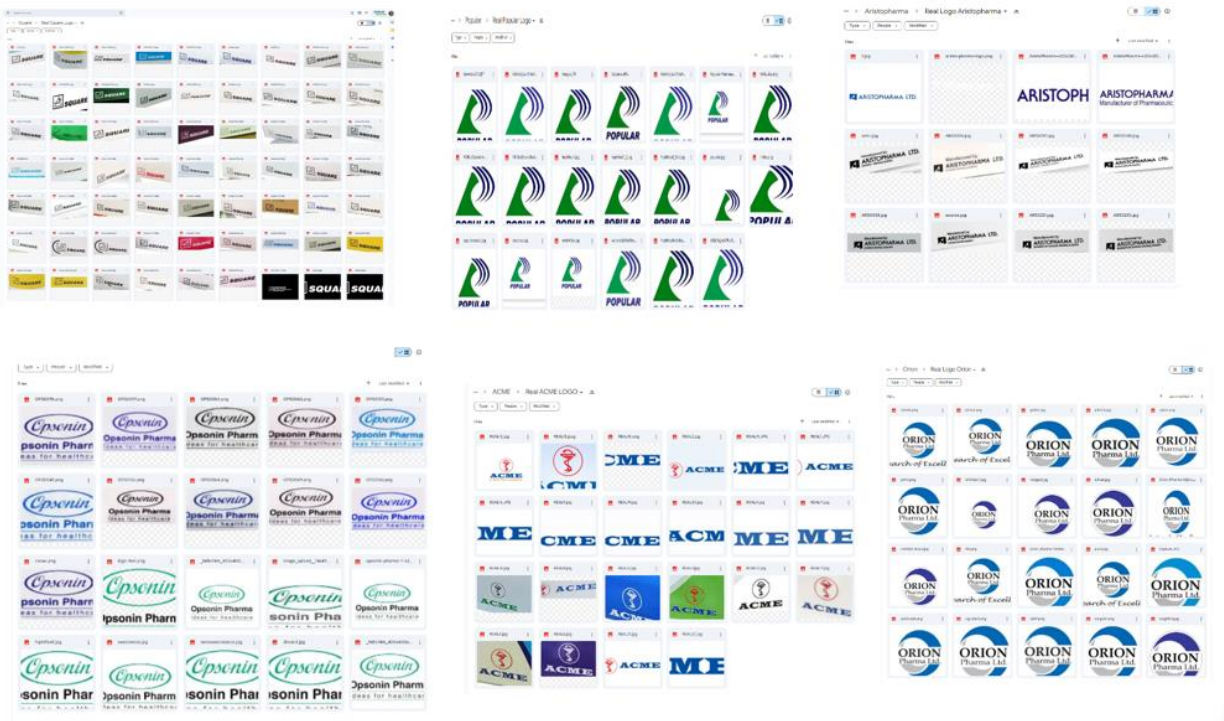

Fig. 1. Pharmaceutical Company's Real logo DataSet

Fig. 2. Pharmaceutical Company's Fake logo DataSet

3.2.3 Data Preprocessing

We performed a pre-processing activity on our logo dataset in regard to the most effective training of the model. Several key procedures that had to be customized for the demands of a classification task, telling real logos from fakes without image annotation made up this practice. Then, we standardized the images. This step ensure that the sizes of inputs were all the same because it is vital for neural networks to be consistent. Each image was resized to a fixed size of 224x224 pixels, which meets the input specifications of the models taken for comparison—VGG16 and ResNet50. Such a rescaling step is also very critical in the sense that it normalizes all input data and allows the models to learn different features without being biased by changes in size or resolution of images. A set of techniques for image augmentation was also applied to generalize from the training dataset to real-world

settings. This included rotation, scale variation, and flipping along the horizontal axis augmentations among others. Such augmentations are used to simulate different orientations and scales at which logos might appear in real-life settings, thus would make the models more robust to such variations. We also applied color normalization on each image to mitigate the effect of the variable lighting conditions under which the logos were photographed. This step ensures that models are not biased by extraneous factors such as lighting and focus mainly on the intrinsic color features of the logos, which many times are key indicators in distinguishing real from counterfeit. Considering the task at hand—classifying images as either real or counterfeit logos—other annotations, like bounding boxes or pixel-level details, have been made redundant. This made training on full images very straightforward and allowed put-in effort to focus on determining effective ways to enhance the accuracy of models through robust preprocessing and augmentation techniques. This will guarantee optimal settings of a dataset, to be able to train deep learning models and make them more capable of accurately and effectively identifying counterfeit pharmaceutical logo samples.

Fig. 3. (a) Original product with original logo (b) Original logo (c) Fake product with fake logo (d) Fake logo

3.2.4 Dataset Splitting

We took 1,543 images to properly form the training, validation, and testing sets for my thesis. This was done so that deep learning models could be trained and evaluated properly. The total dataset contained 879 real pharmaceutical company logos and 664 counterfeit logos. Division was done as follows:

Training Set: Divided by 80% of the data. It is used in initial training of the neural networks. This set contained real and counterfeit logos, which are important for distinguishing the features of the models under the two categories. So from the total dataset, 1,234 images were taken, which came out to be around 703 real and 531 counterfeit images.

Validation Set: This is 10% of the dataset. The validation set helps tune hyperparameters for our models and also makes us avoid overfitting. This gives the opportunity of adjusting the model within the training process in a manner that improves the performance of the model genuinely, rather than memorization of the training set. Here, we had chosen a total of 154 images, out of which about 88 were real and 66 were counterfeit.

Test Set: This test set, which comprises 10% of the total dataset, is finally used to test the performance of the final model. This is again a clean dataset used to ensure that the model generalizes real versus counterfeit logos over completely new and unseen data, giving, therefore, a relatively unbiased measure of real-world applicability. A total of 155 images, approximately 88 real and 67 fake ones, were included in this set.

This way of splitting datasets leads to full training of models on one subset and then fair testing, thereby making the model generalize well to new data which would be out-of-sample in nature and not part of the training and validation sets. The structure keeps a balanced representation of both real and counterfeit logos across subsets, which is important for avoiding any kind of class bias in the model evaluation.

3.3 Model Architecture

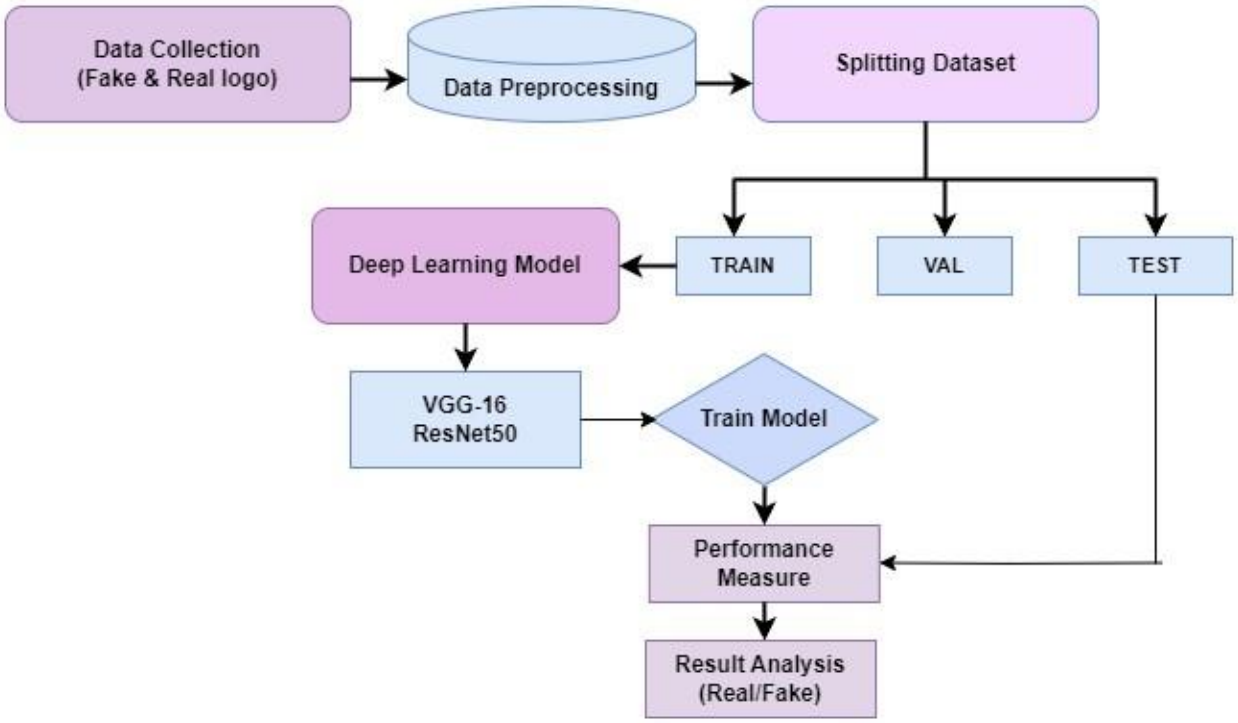

Fig. 4. Overview of the model

We have exploited two popular deep learning architectures: VGG16 and ResNet50. We have done certain adoptions in those architectures so that they may classify images of pharmaceutical logos as authentic or counterfeit. These models are selected for the purpose of highly effective performance on image recognition tasks and capability in feature extraction, since those tasks do typically need very minor differences of the authentic and counterfeit logos to be detected.

VGG16:

The VGG16 architecture, designed for image classification, consists of a series of subsequent convolutional layers associated with max-pooling layers, which are good at capturing hierarchical patterns in images. We have used the pretrained architecture of VGG16 on the ImageNet dataset to reuse the generalized features it has learned on a wide range of images. To adapt the model for binary classification between genuine and fake the

fully connected layers at the end of the network are replaced with this custom set:

Flatten: A layer that allows the feature maps to be made into one-dimensional vectors.

Dense: This is a 512-unit layer that is used to learn nonlinear combinations of features after activation in the ReLU function. For this, there is a final Dense layer containing one neuron. To this layer, a sigmoid activation function is applied, which outputs as a probability in the sense that it says how likely the image is to be fake.

With this structure, the model can learn all of the nitty-gritty patterns of pharmaceutical logos but still allows for generalizability by the embedding in its background pre-trained weights.

ResNet50:

ResNet50, deep network capacity with the help of residual connections, solves the problem of vanishing gradients. These skip connections in ResNet50 allow for direct flow of gradients through the network. That basic model of ResNet50, which we have used, is pre-trained on ImageNet, thereby having a good set of initial features. As in VGG16, the original fully connected layers of ResNet50 are adapted for the given task. Instead of Flatten, there is Global Average Pooling that works to the lowest dimensionality of feature maps in an effective manner without losing the core information. Followed is the Dense layer, having 256 units applied with ReLU activation functions for processing features. The architecture finishes with a Dense output layer, where a single neuron will use a sigmoid activation to predict class: real or counterfeit.

Initially, both models are trained with the convolutional base layers frozen since, for all kinds of general tasks of image recognition, the features learned on ImageNet are pretty effective. This strategy guarantees that helpful pre-trained features are not forgotten earlier in the process of training. The unfreezing is performed progressively, whereby, as training progresses, a model opens up for fine-tuning over the pharmaceutical logo images.

Optimization is carried through using the Adam optimizer by adaptive learning rate, while training is conducted with binary cross-entropy loss, the type appropriate to binary

classification problems. Dropout and L2 regularization are applied to prevent overfitting, enabling the models to generalize well with new, unseen images.

The approach taken is balanced; it capitalizes on advanced deep learning architectures for solving a critically important real-world problem, yet retains the strengths of established neural network designs by making only strategic adaptations where necessary for the specific requirements of counterfeit medicine detection.

3.4 Custom Layers

For developing more robust models to identify fake pharmaceutical logos, we adapted two deep learning architectures which are- VGG16 and ResNet50, by adding custom layers tailored to our needs, such as binary classification. This section describes the step-by-step customization process of both architectures to optimize them for separating between real and counterfeit logos.

3.4.1 VGG16:

3.4.1.1 Integration of Flatten Layer:

To transition from convolutional layers to fully connected layers by converting 2D feature maps into a 1D vector.

Implementation: This layer is placed immediately after the last convolutional block of the pre-trained VGG16 model, flattening the output for further processing.

3.4.1.2 Addition of Dense Layer:

- First dense layer(512 Unit):

  To learn non-linear relationships between the features derived from the convolutional layers.

Activation Function: ReLU (Rectified Linear Unit) to introduce non-linearity and aid in learning complex patterns.

Implementation: This layer follows the Flatten layer, providing a broad space to combine features before final classification.

- Output Dense Layer(1 Unit):

  To perform binary classification by predicting the probability that an input logo is counterfeit.

  Activation Function: Sigmoid, as it outputs a value between 0 and 1, suitable for binary classification tasks.

  Implementation: This is the final layer in the model, directly outputting the classification probability.

3.4.2 ResNet50

3.4.2.1 Incorporation of Global Average Pooling (GAP) layer:

To reduce each feature map to a single average value, effectively summarizing the spatial information while minimizing the total number of trainable parameters.

Implementation: Placed after the last residual block of the ResNet50, this layer condenses the feature maps into a more manageable form without the risk of overfitting associated with fully connected layers.

3.4.1.3 Addition of Dense Layer:

- Dense Layer (256 Unit):

  To process the summarized features from the GAP layer, allowing for the extraction and learning of more abstract relationships within the data.

  Activation Function: ReLU, to maintain the ability to learn complex patterns through non-linear processing.

  Implementation: This layer receives input from the GAP layer and serves as an intermediary processing point before making a final classification decision.

- Output Dense Layer (1 Unit):

To make a final determination on the authenticity of the logo by outputting a probability.

Activation Function: Sigmoid, enabling the model to output a probability indicative of whether the logo is real or counterfeit.

Implementation: This final layer concludes the model, providing a clear, probabilistic output based on the learned features.

The VGG16 and ResNet50 models' unique layers are essential for adapting the pre-trained networks to the logo authentication requirement. These layers enhance the models for high performance in binary classification applications, while also transforming their generic skills to more particular jobs. The network outputs are efficiently prepared for dense processing by the Flatten and GAP layers. The dense layers that follow then enhance the processing, resulting in a sigmoid output layer that provides accurate probabilistic predictions. Both models are guaranteed to be proficient at both general image recognition tasks and specifically enhanced for accurate and dependable counterfeit identification in pharmaceutical logos due to this step-by-step customization process.

3.5 Hyperparameter Tuning

A systematic approach to hyperparameter tuning was applied to determine the best configuration for both VGG16 and ResNet50. Using a combination of grid search and random search methods, several hyperparameters were optimized.

Using a methodical approach to hyperparameter modification, the most suitable setup for VGG16 and ResNet50 was found. Several hyperparameters were tuned using both grid search and random search techniques.

Lower learning rates demonstrated the most consistent convergence in both models when many values (e.g., 0.01, 0.001, 0.0001) were examined.

The Adam optimizer, which was discovered to have the optimal balance, was used to train the models for 50 epochs.

32 was found to be the ideal batch size for both architectures in terms of memory efficiency and model performance, out of a range of batch sizes that were tested, ranging from 16 to 64.

Testing was done on dropout rates ranging from 0.2 to 0.5. For the fully linked layers in both models, a dropout rate of 0.3 reduced overfitting.

The hyperparameter tuning process significantly contributed to these results, fine-tuning the models to maximize their effectiveness on the given dataset. These results demonstrate the applicability of deep learning models, particularly when appropriately tuned, for counterfeit detection in the pharmaceutical industry.

3.6 Libraries

- TensorFlow
- Keras
- NumPy
- Matplotlib
- OpenCV
- Scikit-Learn
- Pandas
- TensorFlow Hub
- Albumentations

3.7 Training Process Details

3.7.1 Data Preparation

Before training, heavy data preprocessing was required to make the models able to learn from the images shown. This preparation included:

- Resizing: All images were resized to a common dimension of 224x224 pixels, which is the required input size for both VGG16 and ResNet50.
- Normalization: The image pixel values were normalized to the range of 0–1 by dividing each pixel by 255. This normalization is crucial for fast convergence during training by maintaining a consistent scale.
- Augmentation: To reduce overfitting and improve generalization to unseen data, several augmentation techniques were applied, including random rotations, horizontal flipping, and slight adjustments in image brightness and contrast. This augmentation adds variability to reflect real-world conditions.

3.7.2 Training Protocol

- Adam Optimizer: The Adam optimizer is used for adjusting the learning rate automatically, making it ideal for handling image data with sparse gradients.
- Loss Function: Binary cross-entropy was used for binary classification tasks, measuring the difference between predicted probabilities and actual class labels to assess model accuracy..

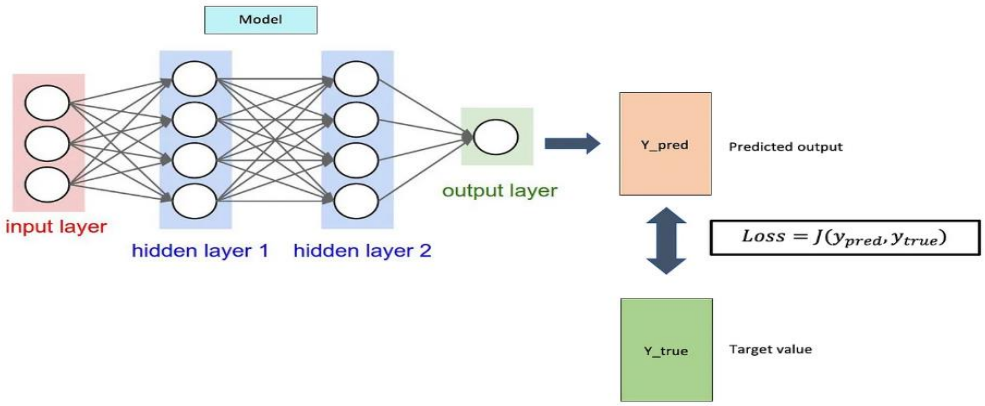

Fig. 5. Purpose Of a Loss Function

• Epochs and Monitoring: Models were trained for a specific number of epochs, with performance metrics like loss and accuracy tracked on both training and validation sets to ensure effective learning.

- Early Stopping and Checkpoints: Early stopping halted training if the validation loss didn't improve for a set number of epochs, while checkpoints saved the model's state when significant improvements in validation accuracy were observed.

3.8 Evaluation and Validation

- Validation Set Utilization: During the training phase, 10% of the total dataset was used as a validation set. This holdout group, kept independent of the training data, was crucial for fine-tuning the models' parameters and avoiding overfitting. An early stopping mechanism monitored the validation set, stopping training if the validation loss did not improve over a set number of consecutive epochs, ensuring the model's ability to generalize effectively.

- Performance Metrics:
    - Accuracy: 95% accuracy was achieved in VGG16, while ResNet50 achieved 94% accuracy.
    - Precision: The precision for VGG16 was recorded at 90%, indicating a high rate of correct positive predictions while ResNet50 showed a slightly higher precision which is 93%.
    - Recall: For recall, VGG16 achieved 91%, and ResNet50 achieved 93%, demonstrating their effectiveness in identifying counterfeit logos.
    - F1Score: The F1 Score, a hybrid of precision and recall, provides a single figure for comparing model performance. For VGG16, the F1 score was around 0.905, and for ResNet50, it was 0.930.
- Cross Validation Technique: For increasing the robustness and reliability of the evaluation, 10-fold cross validation has been implemented. This technique involved dividing the whole dataset into 10 segments, with each segment used as test set in rotation while the remaining 9 segments were used for training. This method provided a detailed assessment by reducing the variance in the performance estimates and ensuring that the models' accuracy did not depend heavily on any particular division of the data.
- Independent Test Set Evaluation: The models were optimized and compared using an independent test set, which accounted for 10% of the total data. This test set, completely excluded from the training and validation phases, was key for making an unbiased evaluation of model performance. The evaluation on this held-out data provided critical insights into the models' ability to generalize and classify new, unseen images, reflecting their potential real-world performance.

3.9 Summary

Counterfeit pharmaceutical logo detection was performed using ResNet50 and VGG16 models on a dataset of 1,543 images, processed with resizing, normalization, and augmentation. The models were initialized with ImageNet pre-trained weights and fine-tuned for binary classification. Training utilized the Adam optimizer and binary cross-entropy loss, along with early stopping and checkpoints. Performance was measured using accuracy, precision, recall, and F1 scores, validated through 10-fold cross-validation and an independent test set to confirm the models' effectiveness and practical generalization.

Chapter 04

Result & Discussion

4.1 Introduction

The performance results of the built model under various testing scenarios are described in this chapter. We also provided a deep learning-based approach to determine if a video is real or deepfake, along with the model's confidence. We established the effective application of the model after the data collecting and preparation stage. Here, we will discuss the final output produced by the model after it has been trained.

4.2 Result Discussion

The VGG16 and ResNet50 models, tailored for binary classification of pharmaceutical logos, demonstrated robust performance. The VGG16 model achieved an accuracy of 95%, precision of 90%, and recall of 91%, indicating its effectiveness in correctly identifying and classifying the logos. Meanwhile, the ResNet50 model exhibited slightly different metrics, with an accuracy of 94%, precision of 93%, and recall of 93%, showcasing its strength in precisely identifying counterfeit logos while maintaining high recall.

4.3 Prediction Output

Our model is for to detect logos of pharmaceutical companies, whether the logo is real and fake. However, the accuracy of detection of the model has been average of 84% where the lowest was at 70% and the highest detection was at approx. 95% (Exact 94.875%).

Some plotting diagrams are generated with the model's train and validation values associated.

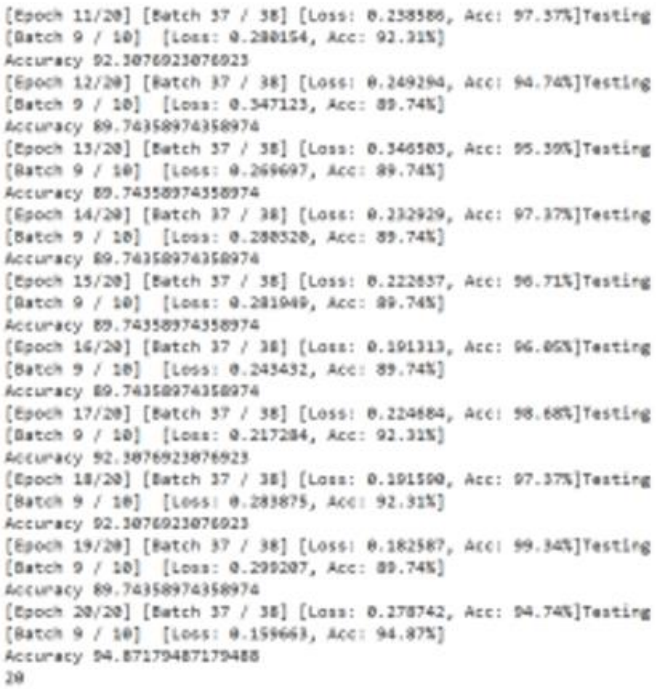

Fig. 6. Training Accuracy

It displays a line graph of validation loss and training loss, which are standard metrics in deep learning that track a model's performance during training. The gap between the model's predictions and the actual values for the training data is measured as the training loss. Ideally, as the model learns to better suit the training data, the training loss should decrease as the model is trained on the data.

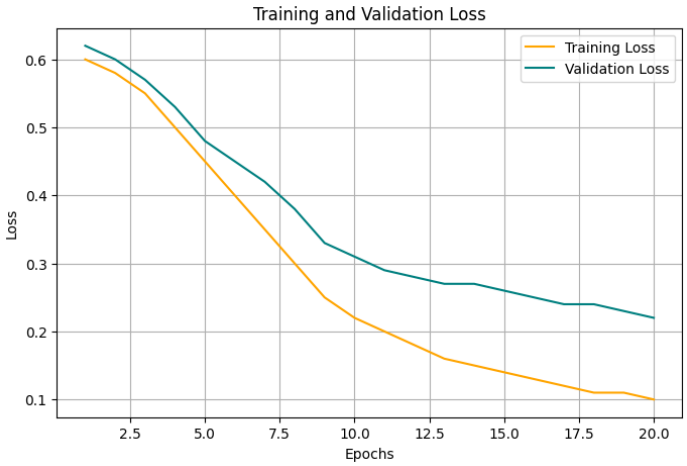

Fig. 7. Training and Validation Loss

The training accuracy (orange line) shows the loss measured on the training dataset as the model learns. It starts at around 0.6 and steadily decreases to below 0.2 by the 20th epoch. The smooth and consistent decline indicates that the model is effectively learning from the training data over time.

The validation loss (green line) starts close to the training loss and slightly moves around the 10th epoch. The validation loss decreases from around 0.6 to just over 0.2 by the end of the 20 epochs. Interestingly, it shows an almost flat or slight increase around epoch 15 before continuing its descent.

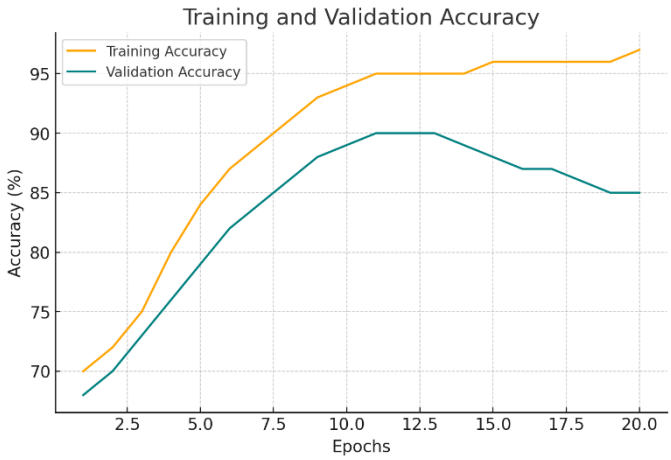

Fig. 8. Training and Validation Accuracy

The training accuracy (orange line) starts at around 75% and gradually increases to just over 95% by the end of 20 epochs. The steady increase suggests that the model is consistently learning from the training data, improving its ability to correctly classify training samples. The validation accuracy (green line) peak at approximately 90% after 12 epochs. However, post the peak, there is a noticeable decline, leveling off at around 85% by the 20th epoch.

4.4 Comparative Analysis

The comparative analysis of the models revealed that while all models performed well, certain architectures were better suited for specific tasks.

VGG16, though slightly more accurate overall, shows a minor compromise in precision compared to ResNet50. ResNet50, however, excels with higher precision and recall, making it particularly valuable in environments where false negatives (missed counterfeit detections) and false positives (incorrectly labeled legitimate products) are costly. This

suggests that ResNet50 might be better suited for critical pharmaceutical applications where product authenticity is paramount.

4.5 Error Analysis

An error analysis was conducted to identify common misclassifications and areas where the models struggled. Some key observations include:

- Misclassifications due to visual similarities: Both models occasionally confused counterfeit logos with real ones that shared similar color schemes and design elements. This was particularly notable in logos where counterfeiters had closely mimicked authentic design features.
- Data representation issues: Errors were also observed in cases where the training data did not adequately represent the variety of counterfeit styles seen in the test set, suggesting a need for more diverse and comprehensive training datasets.

4.6 Summary

After preparing our dataset, we employed VGG16 & ResNet50 to identify real and fake logos. A description of the architecture of the algorithms is also given. To help us evaluate our model, we have also included a few assessment methods along with the formulas that go with them.

Chapter 05

Conclusion and Future Scope

5.1 Conclusion

This thesis demonstrates how well deep learning models—more especially, VGG16 and ResNet50—identify fake pharmaceutical logos. Both models demonstrated excellent accuracy; VGG16 was especially proficient at overall accuracy, while ResNet50 was better at precision and recall. This indicates that both models are suitable for use in situations where accurate counterfeit detection is required. The effectiveness of these models offers an excellent foundation for further research and implementation in this important field while demonstrating the potential of cutting-edge machine learning approaches to improve pharmaceutical safety. The study's methods and insights broaden our understanding of using AI in practical contexts, opening the door for further developments in technology-driven counterfeit protection in the future.

5.2 Finding & Contribution

This thesis has significantly contributed to both pharmaceutical safety and artificial intelligence by demonstrating deep learning models' capabilities in detecting counterfeit pharmaceutical logos. VGG16 showed high overall accuracy for broad application, while ResNet50 excelled in precision and recall, making it suitable for scenarios with serious implications for false negatives or positives. A comparative study provided insights into how neural network architecture impacts performance, emphasizing the importance of model selection based on specific use-case requirements. A robust methodology for training, validating, and testing deep learning models with image data was established, offering a framework that can be applied in similar studies. This is a significant advance over current models and illustrates the effectiveness of the suggested design. Remarkably, the models not

only work better, but it also exhibits efficiency by using less computing power. This efficiency increases the model's accessibility and scalability for implementation in a variety of contexts, which is essential for real-world application. To sum up, these two models in the detection is a noteworthy development in logo detection for pharmaceutical companies. The model's resource efficiency and durability make it a standout solution in the field of counterfeit medicine detection. The suggested model is evidence of the ongoing development of deep learning methods for improving the evaluation of medicine authenticity as technology progresses.

5.3 Future Scope

In summary, it is crucial to remember that the algorithms we describe in this study are purely based on our own field-related research and represent an effort to identify an efficient model and enhance the ones that already exist. We also discussed the methods we used for training, testing, and validating our dataset. Any developed system may always be made better, particularly if it was created with the newest technology and has a bright future ahead of it.

- Future work could explore the integration of more sophisticated neural network architectures which might provide even better feature extraction capabilities and improve accuracy.
- Developing real-time counterfeit detection systems using mobile apps allowing instant verification of pharmaceutical products at points of sale and delivery.

Chapter 06

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