Deep Learning Approaches For Analyzing Microscopic Peripheral Blood Cell Images.

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled **"Deep Learning Approaches for Analyzing Microscopic Peripheral Blood Cell Images"**, submitted by Rafikul Ahsan Rahik, **ID No: 211-15-4050**, and Umme Kulsum, ID No: **211-15-4067** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 12 January, 2025.

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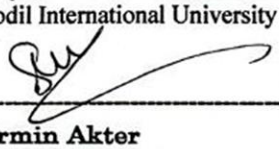

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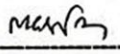

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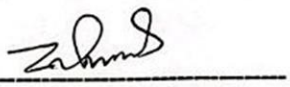

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The diagnosis of numerous hematological disorders depends on the precise and effective classification of peripheral blood cells. However, in high-throughput or resource-constrained contexts, the manual evaluation of peripheral blood smear (PBS) pictures is laborious, prone to errors, and requires expert interpretation. Using a dataset of 17,092 labeled photos, this work explores deep learning techniques to automatically classify eight blood cell types: basophil, eosinophil, erythroblast, immature granulocytes, lymphocyte, monocyte, neutrophil, and platelet. This dataset was used to refine and assess advanced pre-trained models, such as MobileNetV2, ResNet50, ResNet101V2, InceptionV3, VGG16, and EfficientNetB3. MobileNetV2 and EfficientNetB3 were combined to create a hybrid model, which was then improved and assessed. Out of all the models, the Hybrid model had the highest overall accuracy of 95% and the best F1 score of 0.95 on the macro level, and the best loss of 0.15. Most symbolically, the performance of the platelet and eosinophil classes was virtually perfect with the F1-scores of 1.00 and 0.97, accordingly. Even if MobileNetV2 and EfficientNetB3 had a very high efficiency and accuracy, minor deficiencies were revealed for example in immature granulocytes and monocytes classifications; however, Overall all models proposed a fairly high recall. To enhance the results of model generalization and enhance the quality of images, strategies like data augmentation, noise elimination, and image normalization were employed. This research work provides the much-needed confirmation of MobileNetV2 as a very good substitute while providing empirical evidence of the Hybrid Model's ability to scale higher than models trained on a single source in terms of accuracy and robustness. For future works, more efforts will be devoted to creating a larger dataset, refining existing hybrid methods, and enhancing the recall rate of the inferior classification. By enhancing the technique of automatic classification of peripheral blood cells, this work has the potential of developing better and more stylistic clinical and diagnostic arrangements.

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Chapter 1

Introduction

1.1 Introduction

Peripheral blood smear (PBS) is an essential component of diagnostic hematology, enabling or diagnosing various diseases including infections, anemia, and hematological malignancies' detection. Traditionally, skilled pathologists analyze PBS pictures by logging onto the PBS system and visually inspect them in order to determine the size, shape, and distribution of blood cells. Hand inspection works, but it is time-consuming, labor-intensive, represents subjective judgment, requires important knowledge, and hence does not work for large-size/high-volume or maximum-scale displays. Furthermore, changes in picture quality and staining procedures add difficulties to this diagnosis. Subfields in machine intelligence, especially deep learning, have progressed to revolutionize the field of analysis of sight medical images, where automatic and precise approaches replace traditional workmanship labor needs that previously succumbed to human expertise. There is a promise demonstrated earlier using pre-trained convolutional neural networks like MobileNetV2, InceptionV3, ResNet50, VGG16, ResNet101V2, and EfficientNetB3 for feature extraction and classification. Building on these developments, this work presents a Hybrid Model that enhances classification performance by combining MobileNetV2 and EfficientNetB3, utilizing their respective capabilities. By automating the classification of eight significant blood cell types: basophil, eosinophil, erythroblast, immature granulocytes, lymphocyte, monocyte, neutrophil, and platelet, this study applies state-of-the-art models to address the challenges of PBS analysis. By using contemporary preprocessing techniques, thoroughly evaluating the efficacy of these models, and introducing a unique hybrid model for better diagnostic results, this study seeks to establish a robust, scalable framework for automated hematological diagnosis.

1.2 Motivation

This work is motivated by the increasing need for quick and precise hematological diagnostics. Clinical laboratories are dealing with increased workloads as a result of the rising prevalence of blood-related illnesses and the requirement for prompt diagnosis. PBS analysis done by hand takes a lot of time and is subject to observer bias, which might provide contradictory results. These drawbacks demonstrate that automated and standardized methods are sorely lacking, mainly to enhance blood cell categorization speed as well as accuracy. Deep learning is the computational aspect behind this study: the tremendously rapid progress of a method that has enormously enhanced medical image analysis by enabling definitive, automated feature abstraction, and classification. MobileNetV2 and EfficientNetB3, seen as strong

scalable and efficient models, offer solutions for usage in contexts that have restricted accessibility and when the available computing platforms are limited; that makes these models perfect to be used in low-resource scenarios or restricted mobile platforms. To increase accuracy and efficiency even more, we introduce a model that takes the best from both MobileNetV2 and EfficientNetB3. This work also increases the availability of advanced diagnostic technologies, notably in developing regions, and optimizes diagnostic processes through the use of automated blood cell classification. It is thus raising machine learning diagnostic reliability without over-depending on skilled pathologists to decrease significant gaps in healthcare provision and achieve inequality of hematological diagnostics everywhere.

1.3 Objectives

The main objectives of this paper are:

- Create an automated method for classifying peripheral blood smear pictures into eight categories: basophil, eosinophil, erythroblast, immunoglobulin, lymphocyte, monocyte, neutrophil, and platelet.
- To assess and compare the performance of Seven pre-trained deep learning models: MobileNetV2, InceptionV3, ResNet50, ResNet101V2, VGG16, EfficientNetB3, and Hybrid model on a big dataset.
- Determine the best-performing model using criteria like accuracy, precision, recall, and F1 score.
- Optimize preprocessing and augmentation approaches to increase model generalization and deal with dataset variability. Evaluate the scalability and computing efficiency of lightweight models in real-world applications.

1.4 Methodology

Using a dataset of 17,092 labeled pictures divided into eight blood cell types, the technique for this work concentrated on creating and assessing automated classification models for peripheral blood smear images. The data was divided into subgroups for testing (20%), validation (10%), and training (70%). 224 × 224 pixel images were scaled, normalized to scale pixel values between [0, 1], and then treated with Gaussian and median filtering, two methods for reducing noise. Evaluations were conducted on seven deep learning models, including MobileNetV2, InceptionV3, VGG16, ResNet50, ResNet101V2 EfficientNetB3, and a hybrid model that combined the two. With a learning rate of 0.001, a batch size of 32, and training epochs of 20 for lightweight models (MobileNetV2, VGG16) and 50 for more complex architectures, the models were trained using the Adam optimizer. Overfitting was avoided by applying early stopping. Each class's performance metrics: accuracy, precision, recall, and F1-score, were computed, and overall performance was assessed using weighted averages and macro. With 95% accuracy, a macro F1-score of 0.95, and a loss of 0.15, the Hybrid Model outperformed all other models and showed the best outcomes. In order to ensure scalability for practical applications, experiments were carried out on Google Colab with GPU acceleration. This technique demonstrates a sound strategy for developing effective and scalable automated hematological diagnostics systems.

1.5 Project Outcome

The following are the anticipated results of this study:

- A strong automated blood cell classification system that can accurately categorize peripheral blood smear pictures into eight different classes: platelets, neutrophils, erythroblasts, basophils, eosinophils, immature granulocytes, lymphocytes, and monocytes.
- The top-performing model was determined to be Hybrid, which maintained computational efficiency while delivering a balanced performance with excellent accuracy, recall, and F1 scores.
- A better comprehension of how preprocessing methods, including augmentation and HSV transformations, may improve the accuracy and generalization of the model.
- To ensure balanced model performance across all categories, class-specific problems and solutions are identified in order to enhance memory for underperforming classes, such as monocytes and immature granulocytes.

Creation of a resource-efficient and scalable system that supports quicker and more precise hematological diagnostics and can be implemented in clinical settings and surroundings with limited resources.

1.6 Organization of the Report

The six chapters that make up this report's format each focus on a different facet of the research.

Chapter 1: Introduction, A summary of the study issue is given in this chapter, together with information on the background, motivation, goals, methods, and anticipated results. It also describes the report's format.

Chapter 2: Background, This section examines previous research, relevant applications, and literature. It lays the groundwork for the investigation by defining the problem's extent and pointing up information gaps.

Chapter 3: Research Methodology, The study strategy, including data collecting, preprocessing methods, and the methodology used for model training and assessment, is covered in length in this chapter. It also draws attention to the resources and tools that were employed.

Chapter 4: Experimental Results and Discussion, In this section, the authors discuss the experiment scenario and results, and evaluate the simulated results and model performance. It provides an evaluation of the results achieved and also a comparison between the models.

Chapter 5: Consequent to the findings therefore is the acknowledgment of the larger implications of the study, with clear reference to sustainability concerns alongside the societal, ethical, and environmental angles that surround the study.

Chapter 6: In the last chapters, the results are concluded, and proposals for the next research are given.

Chapter 2

Background

2.1 Introduction

A large array of health problems can be investigated by studying blood cells, starting with infections and ending with hereditary blood clotting disorders; red blood cells (RBCs), white blood cells (WBCs), and platelets. For example WBC can tell you leukemia or immune systems related complication while RBC morphology is crucial in anemia [1]. The older, conventional methods of performing hematological analysis involved the examination of pictures of the peripheral blood smear (PBS), which is an exhaustive, excessively time-consuming and tedious process, that also demands expertise. The last few years of research focus on deep learning (DL) for the analysis of pictures acquired by PBS due to the limitations of the manual assessment. This technology has shown the potential of diagnosing blood diseases such as anemia and leukemia faster, accurately, and without variation [3,4]. However, there are some problems with deep learning for microscopic blood cell analysis even with the encouraging results. Most approaches usually encounter problems stemming from variation in staining methods, cell geometry and quality of pictures. Moreover, user segmentation is still challenging concerning proper separation of overlapping cells and classification of visually similar subtypes that, in turn, often generate contradictory results [5,6]. Year-long variations further affect the generalization and reliability of the model, applied to functional clinical practice, due to the inconsistency of data originating from various visualization techniques. Negative models affect ability to diagnose and endanger patients in those regions where automated solutions will be the most useful in the context of areas with limited resources – such gaps should be filled [7,8]. To clarify this gap in knowledge, this paper presents an extensive review of deep learning models with a focus on the segmentation and classification of PBS images of blood cells. The present study is based on the recent advancements by proposing the method of the integration of SVM with CNN and selection of appropriate features for feature extraction and classification enhancing [9,10]. The segmentation alogorithm proposed is created for the specific shape of blood cells, while the picture pre-processing can be used to overcome any of the quality problems met in the developing phase. This research is aimed to develop the proper foundation for defining the PBS pictures as accurately as possible using modern CNN-based structures in combination with advanced image processing and features extraction techniques, which will enhance the diagnostic accuracy in the hematology subspecialty. Finally, this research seeks to present a model that addresses some of the challenges in data variation and segmentations that are in this field to advance deep learning methods in blood cells classification. Based on the enhancement of the availability of automated hematological analysis and the enhancement of diagnostic speed and homogeneity of this method, it is believed that this method is a competitive

substitute for blood smear examination.

2.2 Literature Review

Mundhra et al. [11] developed a new automated system, called Shonit™ for the analysis of peripheral blood smear images. To support the classification and localization of the primary blood cell types for RBCs, WBCs, and platelets in microscope pictures to localize them into a specific region of the pictures, our system utilized a deep learning model together with a U-net model for segmentation. It was possible to sort about 30,000 RBCs and 5,000 platelets under various staining and imaging conditions since the dataset was a diverse set of blood smear samples. Shonit™ was a great accuracy shown from the results with over 98% specificity and 91% sensitivity of cell-type identification. Its performance was limited due to the need for fine-tuning in the case of classifying blood smear images that were produced using different methods, and it was affected by variations in picture quality.

Hegde et al. [12] investigated a comparison of deep learning methods with conventional image processing methods for the classification of white blood cells (WBCs) in peripheral blood smear pictures. While deep learning models, such as convolutional neural networks (CNNs) and autoencoders, used supervised and unsupervised learning approaches, traditional methods required a sequence of segmentation and feature extraction processes. 1,159 of the 1,418 cropped photos in the dataset were utilized to train the CNN model. The small dataset size was addressed through the use of data augmentation. The CNN model outperformed the conventional methods with an astounding accuracy of almost 99%. However, in addition to the constraints imposed by the limited dataset, the study observed difficulties in the deep-learning models because of the noise and light changes found in the microscopic pictures.

Alzubaidi et al. [13] suggested deep learning models that are lightweight and especially aimed at improving the diagnosis of sickle cell anemia by identifying red blood cells in microscopic pictures. Domain-specific transfer learning and data augmentation were used to create three distinct convolutional neural network (CNN) architectures that addressed the scarcity of labeled sickle cell data. Three kinds of red blood cell pictures were found in the dataset, which was derived from the erythrocytesIDB dataset and two other blood smear datasets. These categories were circular (normal), elongated (sickle cells), and other blood content. The models reached state-of-the-art classification accuracy with data augmentation, achieving 99.54% on the erythrocytesIDB dataset and 98.87% on a different gathered dataset. Adding a multiclass SVM classifier further improved performance. To achieve the stated high accuracy, however, transfer learning and augmentation approaches were required because the deep learning models were limited by the tiny datasets provided.

Tseng et al. [14] investigated the use of deep learning models to classify mature and immature neutrophils from peripheral blood smears. Ten CNN models, such as DenseNet and ResNeSt, were used in the study to categorize six different kinds of neutrophils from pictures taken with different imaging equipment. Training efficiency was increased by using transfer learning, and model evaluation on a variety of datasets showed an average testing accuracy of 90.1%. For the six classes, the sensitivity and specificity were over 83.5% and 96.9%, respectively. Despite the encouraging accuracy, it was pointed out that

more improvements were required to increase generalizability across datasets from various sources.

Chola et al. [15] created BCNet, a deep learning framework for peripheral blood cell multi-class identification, to provide quick and accurate diagnostic assessments. When BCNet's performance was evaluated using transfer learning versus well-known models like as DenseNet and ResNet, it achieved an accuracy of 98.51% using the RMSprop optimizer. With significant gains in prediction times, BCNet outperformed other models in terms of processing speed and accuracy. However, what the investigation established was the fact that the optimization was still open for further optimization because of the detailed structure of the optimizer resulting to extensive computation time beside to the fact that the variability of the results would depend on the type of optimizer that would be used.

Phuong Et al. [16] Based on SegNet architecture for semantic segmentation of RBCs and WBCs from blood smear pictures to propose an idea of an autonomous blood cell counting system. After segmentation, cell separation, and counting were done using the Euclidean distance transform and linked component labeling methods that yielded the counting efficiencies of 97.38% WBCs and 93.3% RBCs. While the study revealed cell overlap or major differences in picture quality raised accuracy concern, this approach provided a suitable method to hand counting, requiring enhancement in cell separation methods.

Navya et al. [17] discussed the automation of peripheral blood smear (PBS) analysis for the detection of anemia from the pictures of red blood cells (RBCs) in detail. The methods were divided into three categories: detection of anemia situations, classification and segmentation of RBCs. While a number of methodologies such as Otsu thresholding, Watershed, and machine learning algorithms created superior segmentation and classification rates, the study also revealed that a manual approach was time-consuming and error-sensitive methodologies. Due to inability to clearly differentiate between conflating RBCs and differentiating between cells that are morphologically similar, the study was limited and it was postulated that more appropriate models are needed for some forms of RBC pathology.

Raheel et al. [18] proposed a deep learning method to categorize the leukemia from tiny blood smear pictures without any need of high resolution pictures by using a special convolutional neural network (CNN). To increase the resolution of an image, the authors applied several methods to a set of 4150 images excluding noise, adjusting the contrast, and erasing the background. In order to get better feature representation, two CNN models CNN-1 and CNN-2 were trained, and the features of these two models were combined using CCA. h, the Bagging ensemble classifier was most accurate with the test accuracy of 97.04%. The following were found to be limitations: • Because of the complex nature of feature extraction, an attempt at using high-resolution photos as the input is likely to be plagued with background noise.

Almurayziq et al. [19] has also investigated practical ways through which the identification of classification of white blood cells (WBCs) through deep and hybrid learning methods in order to diagnose illnesses in WBCs at an early stage. Cohort of twelve thousand five hundred and seven microscopy images were preprocessed by retraining architectures of AlexNet, ResNet-50, ResNet-18, and GoogLeNet and were then classified using SVMs achieving an all-high accuracy of 99.3% in medical diagnosis using ResNet-50 architecture. Issues that arose on account of staining methods affecting differential WBC pictures and the risk of deep learning models developing data specificity limitations, which became

limitations of this study, highlighted the need for further validation.
Zolfaghari et al. [20] describe computer-aided methods for distinguishing and categorizing white blood cells and acute leukemia and categorizing them as follows: The categories include a hybrid approach, deep learning technique, and the traditional method. The two methods distinctively are used prominently; models up to 99.2% accuracy with SVM and over 99% accuracy with CNN. The study also shows that there is potential to enhance the results by adopting both CNN and SVM at the same time. One disadvantage of certain traits is the reliance on them, and the second, is the computation cost; this work's recommendation for future studies is to develop more complex organic CNNs for higher accuracy and lower computation costs.

2.3 Gap Analysis

There are still a number of difficulties that highlight important gaps in the present research and applications, even with the notable advancements in the use of deep learning for peripheral blood smear categorization. The underrepresentation of several blood cell types in the training datasets, such as immature granulocytes and monocytes, results in a significant gap in recall and accuracy for these classes. Although class-weighted loss functions and data augmentation have been investigated, additional study is required to provide more efficient methods for enhancing recall for underrepresented classes and balancing class performance. The generalization of models represents another gap. On some datasets, deep learning models like ResNet and MobileNetV2 exhibit encouraging results; but, when applied to a variety of real-world datasets with varying imaging circumstances, staining processes, and quality differences, their performance may deteriorate. In order to generalize across these variances without overfitting, models must be sufficiently resilient. Furthermore, model interpretability is still a problem. Even though a lot of deep learning models are quite accurate, clinical adoption of these models depends on knowing how and why they produce particular predictions. Therefore, to further enhance openness and confidence in these models, future studies need to consider explainable AI methods, namely Grad-CAM and SHAP. Finally, there is a gap in the scalable and deployment approach where the resources are limited. However, for deploying such lightweight models as MobileNetV2 in a range of clinical environments such as cloud-based services and mobile platforms in connection with the utilization of tools aimed at automated classification in contexts of remote or underprivileged areas with lower computational power, other optimization is needed. To fill these gaps, the current work will employ complex preprocessing, introduce the Hybrid Model, and discuss how to enhance the interpretability, class balance, and model transferability.

2.4 Summary

Further, the ever-increasing application of deep learning methods in clinical diagnosis was also discussed in this section with special emphasis on the possibilities of the extraordinary role of deep learning in hematology. A variety of studies has underlined the effectiveness of using pre-trained models for the classification of blood cells since they potentially help in the automation of this diagnosis. These models have supplemented the area with

architectures like MobileNetV2 and ResNet that offer a high accuracy rate and work efficiently as compared to the conventional approach that is mostly based on the analysis done by human analysts. The benefits of using a number of pre-trained networks and the possibility of hybrid models where many pre-trained networks are combined with the idea that improving one aspect always sacrifices another aspect were also discussed. All in all, these models are very useful as I was facing many problems in achieving suitable accuracy using imbalanced data sources and different types of blood cells. It is also a focus of growth as these models are increasingly integrated into web and mobile applications, to produce quicker diagnosis and more accessibility in the developed world and newly industrializing nations. Different preprocessing approaches were discussed as means of addressing issues, including class imbalance and dataset volatility. What this does is improve the models' robustness and ensure reliable performance in practice applications require this. In any case, it grounded the research by outlining the current state of automated blood cell categorization, identifying some major challenges, and explaining how the proposed Hybrid Model aims to address them.

Chapter 3

Research Methodology

3.1 Methodology

3.1.1 Overview

Using deep learning models, the technique focuses on creating an automated system that can categorize peripheral blood smear pictures into eight different categories of blood cells. The method starts with preprocessing and data-gathering methods to make sure the pictures are ready for model training. Normalization, noise reduction, and standardization are preprocessing techniques that enhance the quality of the incoming data. In the following step, six pre-trained deep learning models are selected for evaluation: MobileNetV2, ResNet50, ResNet101V2, InceptionV3, VGG16, and a Hybrid Model that combines MobileNetV2 and EfficientNetB3. Using the provided dataset, these models are refined to identify the top-performing model in terms of accuracy, precision, recall, and F1 score. Each model's computational requirements are examined using requirement analysis, which takes resource efficiency and processing power into account. Particular focus is placed on models that may be implemented in contexts with limited resources, like MobileNetV2, which guarantees scalability and affordability for low-resource and portable applications. Thus, the design specification described in the paper provides a basis for integrating these models into an automatic categorization system by explaining the system architecture, data flow, and assessment procedures. This approach is intended to ensure two things – high quality of the result and real possibilities of practical application of the diagnostic technology in medicine, opening the path towards diagnostic applications.

3.1.2 Proposed Methodology

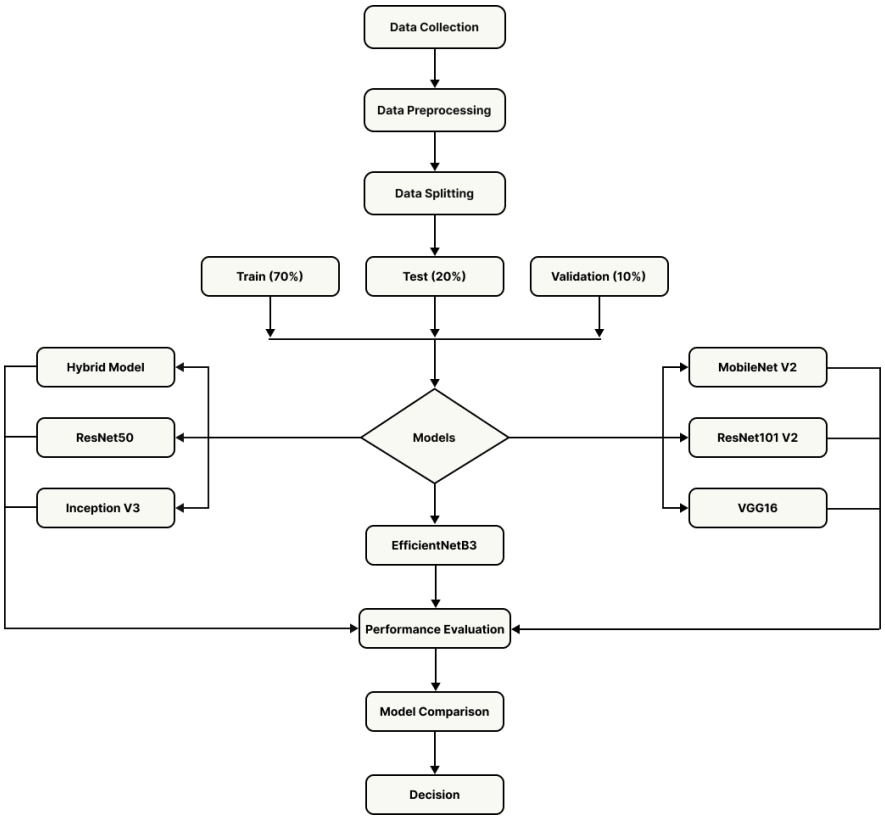

Figure 3.1: Workflow diagram

- Data Collection: assemble 17,092 pictures into a tagged dataset.
- Data Preprocessing: Use contrast stretching, Gaussian filtering, and Laplacian sharpening.
- Data Splitting: Divide the dataset into three categories: test (20%), validation (10%), and training (70%).
- Model Training: Use the provided dataset to train models.
- Model Evaluation: Assess MobileNetV2, ResNet50, ResNet101V2, InceptionV3, VGG16, and the Hybrid Model's performance.
- Model Comparison: Examine models according to their F1 score, recall, accuracy, and precision.
- Performance Evaluation: Examine and evaluate the models' advantages and disadvantages.
- Final Decision: The best option for categorization is the Hybrid Model.

3.1.3 Model Description

MobileNetV2: A highly scalable and efficient computing convolutional neural network is called MobileNetV2. It is suitable for mobile and edge devices because its deployment effectively halved the number of parameters and computation through depthwise

separable convolutions. As for the architecture, it is optimal for scenarios with restricted resources because of its balanced characteristic, performance and efficiency.

ResNet50: ResNet50 explains the vanishing gradient problem of deep architectures by involving a 50 layer deep convolutional network of residual connections. Since this approach has the ability to decode delicate attributes within mandatory sets of complicated illustrations, it is often used for image classification problems. The architecture of deeper networks is quite robust and hence, deeper networks are amenable to being trained.

ResNet101V2: ResNet 101V2 is actually a variant of ResNet and it has 101 layers in it. Through the reduced susceptibility to approaching a saturation point due to using of modern normalizing techniques, the original ResNet is improved and serves convergence and performance improvements. That is why it is most suitable for picture analysis, mainly because of the depth it has been built to capture each detail.

InceptionV3: InceptionV3 is a DCNN that employs inception modules in order to optimize analyzing time and other computational parameters. These modules successfully generalize features from photos due to the multiple filter sizes which are combined together to gather characteristics on different scales. It is particularly noteworthy that image categorization and virtually all the other applications of computer vision are served well by its modular structure.

VGG16: VGG16 is a 16 layer deep convolution neural network which was designed with simple convolution blocks and a consistent architecture. Due to the architectural structure of the layer there is the possibility to extract hierarchical characteristics because it is deeper rather than wider. It is one of the simplest algorithms and also is comparatively successful in picture categorization applications.

EfficientNetB3: A convolutional neural network increases depth, breadth, and resolution with the aid of compound scaling factors makes it efficient and effective. Consequently, it has proven useful for difficult picture classification tasks because it is economical in computation while providing optimal feature extraction. It varies in a proportional manner in all its aspects, which make it possible for it to handle a number of datasets and requirements.

Hybrid Model (MobileNetV2 and EfficientNetB3): The proposed Hybrid Model fuses the heavy feature extraction ability of EfficientNetB3, and the light network efficiency of MobileNetV2. The potential of this architecture is evident in scalability and versatility, suitability both in resource-intensive and resource-limited environments as the designs attempt to optimize both computational expense and payoff. The Hybrid Model is a balance and efficient blood cell categorization solution since it retains the strengths of the two models.

3.2 Detailed Methodology and Design

Currently, the first steps in the methodical process for using peripheral blood smear picture classification are involved in the data collection and preparation for their analyses. To support the appropriate assessment of the model, the data set was divided into three sets, 70% for training, 10% for the validation of the results, and 20% for testing the final models. Here, the photographic images were interpolated to 224 pixel by 224 pixels plane for focusing procedure prior to applying a variety of methods including, contrast enhancement to boost image contrast, Gaussian elimination to reduce noise and Laplacian

to enhance cell edges. To enhance the predictive capabilities of all the models applied within the given study, the procedures mentioned herein were employed to accentuate significant characteristics of the cells in question while minimizing noise and unevenness. For this task, seven already trained models including MobileNetV2, ResNet50, ResNet101V2, EfficientNetB3, InceptionV3, VGG16 and a combined model of MobileNetV2 and EfficientNetB3 have been chosen. This is the case of MobileNetV2 was chosen for implementation due to its lighter design and the ability to consume limited computational resources. All the same, some peculiarities of ResNet50 and ResNet101V2 were considered while drawing the scheme working capacity for real-time applications remained limited due to increased computing demands. Also tested were InceptionV3 and VGG16, though the two were less scalable due to the high processing power needed. The Hybrid Model was therefore developed to enhance performance with specific retention of computational efficiency drawn from MobileNetV2 and EfficientNetB3 models. The models were trained for 50 epochs for heavier models and 20 epochs for lighter models including MobileNetV2 using an Adam optimizer at a learning rate of 0.001. To control overfitting, the approach of early stopping was used during trials. As the figures of merit that characterized the performance of the models, the accuracy, precision, recall and F1-score were employed. rates of total accuracy of the patterns from the classes and the Hybrid Model as the highest total accuracy of 95 percent were established to equal the best option for blood smear categorization. Thus, the benefits of this technique are the possibility of practical application in healthcare, compared with the results obtained by other specific techniques in the framework of other types of tasks, paying attention to achieved productivity and scalability performance.

3.3 Project Plan

Thus, the project plan was developed in order to ensure the systematic approach towards tasks accomplishing and utilizing of the resources available. It should be noted that the Data preparation was among the initial steps of the project before proceeding with other stages that included; Model selection and training as well as model assessment. Limiting the complexity and once again with assistance from the first stage it was identified that in order to enhance the picture quality, further pre-processing steps include contrast stretching, Gaussian filter and Laplacian filter were applied. Six pre-trained models were then refined for the categorization of eight blood cell types: MobileNetV2, ResNet50, ResNet101V2, InceptionV3 and VGG16 based models and the proposed Hybrid Model. Google Colab was used to train and evaluate the data and also allow for GPU acceleration for handling data. The final stages involved evaluating the model results, documenting the results and integrating them into a large report while also incorporating ideas into this large report. This guaranteed that at every stage of the development, the respective members of the team were in harmony with each other and that problem solving was efficient. Some of the achieved tasks included data preprocessing, model training, model evaluation and performance reporting and report writing and finalization.

3.4 Task Allocation

In order to ensure better workflow and the fact that all tasks are divided between two team members, different project duties were assigned to two members of the team:
Member 1: Kept on working to maintain a specific model training, coding and model execution.
Member 2: Involved in writing the paper, and helped with coding were necessary in order to record the results.
Everyone on the team backed up the other while writing the code and ensured that each phase of the project was completed with relative ease.
They suggest that the cooperative scheme ensured on timely completion of duties and a successful end to the project.

3.5 Summary

In this section, the idea and strategy for designing an automated classification system of blood cells through deep learning models are presented. The examination started with data acquisition and further preparation of the required data set; for enhancement of the picture contrast stretching, Gaussian filter, Laplacian filter sharpening techniques has been used so that the important aspects of blood cells morphology were visible at best. For the purpose of model training and evaluation, the image set was split into training, validation, and testing sets with proportions of 70%, 10% and 20% respectively and contained 17,092 tagged photos illustrating eight types of blood cells. Six pre-trained models which were tested include; MobileNetV2, ResNet50, ResNet101V2, InceptionB3, VGG16, and a combined model of MobileNetV2 and EfficientNetB3. Each model was trained and fine-tuned to have an excellent skills level of classification so that they would be very efficient computationally. To bring the best of both worlds when it comes to performance optimization and scalability, the MobileNetV2 and EfficientNetB3 models formed the basis of the Hybrid Model and it was designed for MobileNetV2's lightness, and EfficientNetB3's superior feature extraction. Implementation was achieved due to the existence and aggressive project plan and jobs specification to ensure that everyone has his/her task description in the project. The total strategy is adaptive, moderate between the computing loads and scales of accuracy needed, which makes it ideal for confined environments and real clinical uses. This detailed approach solves problems in medical diagnosis based on advanced AI techniques and provides a basis for developing a reliable and translational system for blood cell classification.

Chapter 4

Implementation and Results

4.1 Environment Setup

Here Table 4.1 represents the Experimental Setup and Table 4.2 represents Data splitting.

Table 4.1: Experimental Setup

Process Name	S. N.	Action
Input	1	Gathered pictures of eight different kinds of blood cells for categorization.
Environment Configuration	2	Using Google Colab and imported the required dependencies and libraries.
Directories	3	Grouped pictures into sets for testing, training, and validation (10% for validation).
Model Training	4	Utilizing transfer learning, MobileNetV2, ResNet50, ResNet101V2, InceptionV3, VGG16, and Hybrid Model were refined.
Model Compilation	5	Models were built using the Adam optimizer, with a learning rate of 0.001 and validation loss tracked.
Performance Evaluation	6	Assessed loss reports, F1-score, recall, accuracy, and precision.
Prediction	7	Random photos were used to test models and verify predictions.

Table 4.2: Dataset Splitting

S. N.	Class Name	Count	Train (70%)	Test (20%)	Validation (10)
1	Basophil	1218	853	244	121
2	Eosinophil	3117	2182	623	312
3	Erythroblast	1551	1086	310	155
4	Immature Granulocytes	2895	2027	579	289
5	Lymphocyte	1214	850	243	121
6	Monocyte	1420	994	284	142
7	Neutrophil	3329	2330	666	333
8	Platelet	2348	1644	470	234

4.2 Performance

4.2.1 Evaluation Metrics

Moving on to the confusion matrices for the models, it presents information about accuracy of their classification performance: MobileNetV2, ResNet50, ResNet101V2, InceptionV3, VGG16, EfficientNetB3, and the Hybrid Model. MobileNetV2, depicted in figure 2, yields a satisfactory identification rate in all classes and low false positives and false negatives rates but the dominant classes are platelets, eosinophils and neutrophils. Depending on the size of the particles which are significantly different in terms of color, ResNet50 yields the confusion matrix presented in Fig. 3 wherein it distinguishes properly neutrophils and eosinophils but is a bit confused about immature granulocytes and basophils with higher misclassification rates. In the case of platelets and eosinophils, the model is capable of good feature extraction, achieving good accuracy; for monocytes and immature granulocytes, the model incurs a high false positive and false negative rate (Figure 4). Similar to this, InceptionV3's confusion matrix (Figure 5) illustrates how well it detects dominant classes but struggles with monocytes and immature granulocytes, which lowers recall for these groups. Figure 6 shows that VGG16 performs consistently across the majority of classes, however, it has trouble accurately identifying monocytes and basophils, which have higher mistake rates. Although Figure 7, which represents EfficientNetB3, effectively handles dominating classes like neutrophils and eosinophils, there is still a need for improvement due to sporadic misclassifications in monocytes. The Hybrid Model, seen in Figure 8, has the most balanced performance across all blood cell types, successfully resolving issues in physically comparable but underrepresented groups such as immature granulocytes and monocytes. Together, these confusion matrices show the advantages and disadvantages of each model, highlighting the necessity for sophisticated methods to enhance the categorization of difficult classes while preserving computational effectiveness.

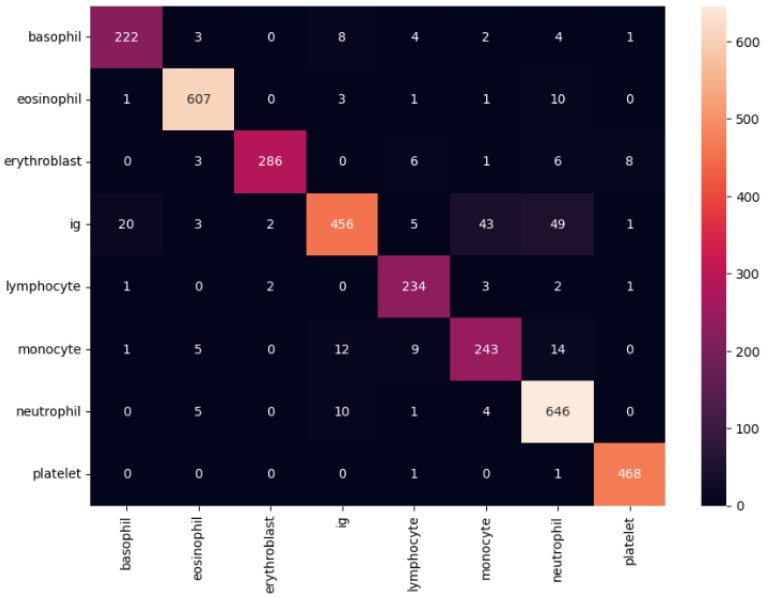

Figure 4.1: Confusion matrix of MobileNetV2 model

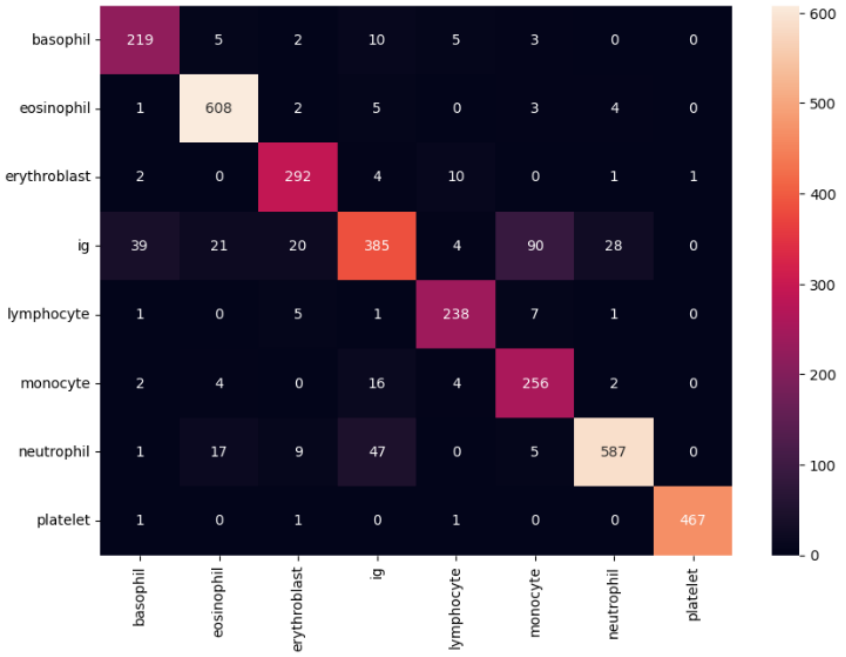

Figure 4.2: Confusion matrix of ResNet50 model

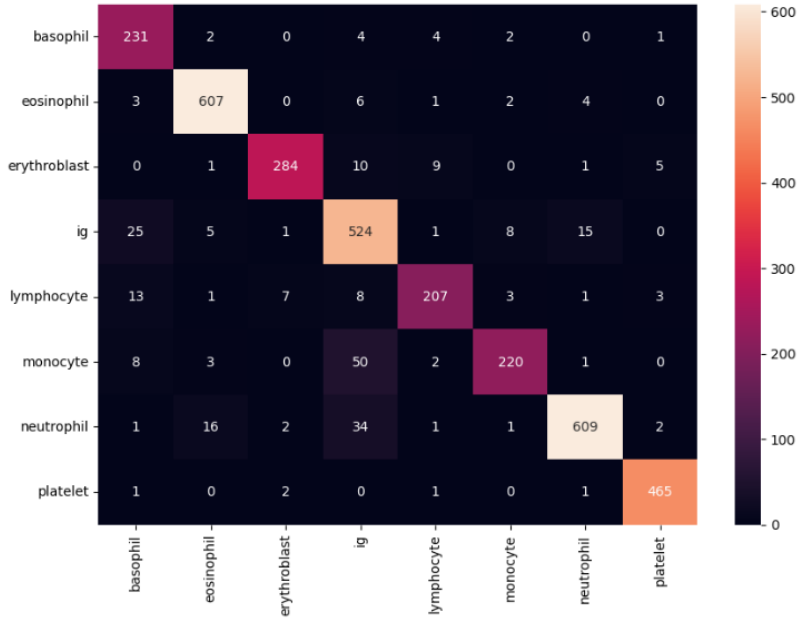

Fig 4.3: Confusion matrix of ResNet101V2 model

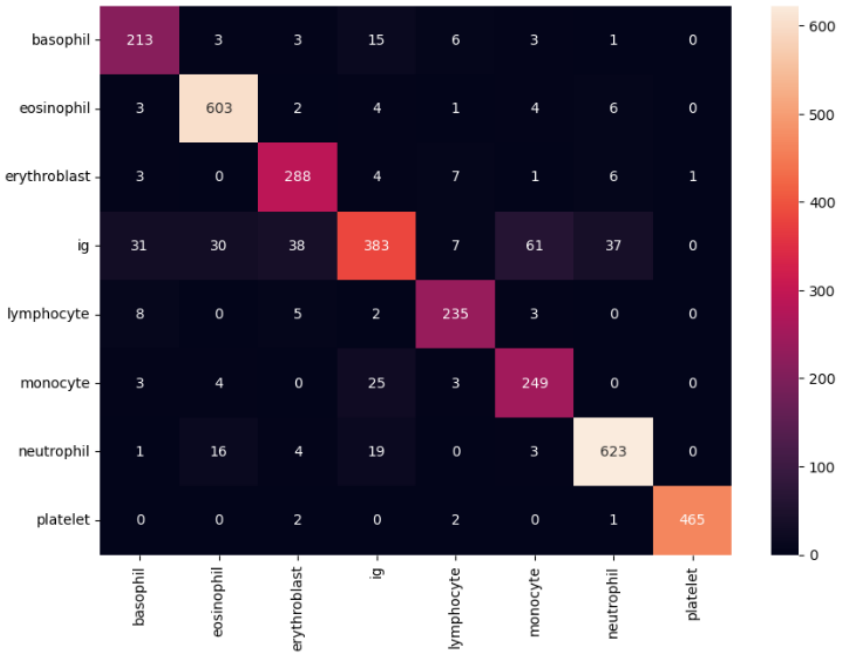

Figure 4.4: Confusion matrix of InceptionV3 model

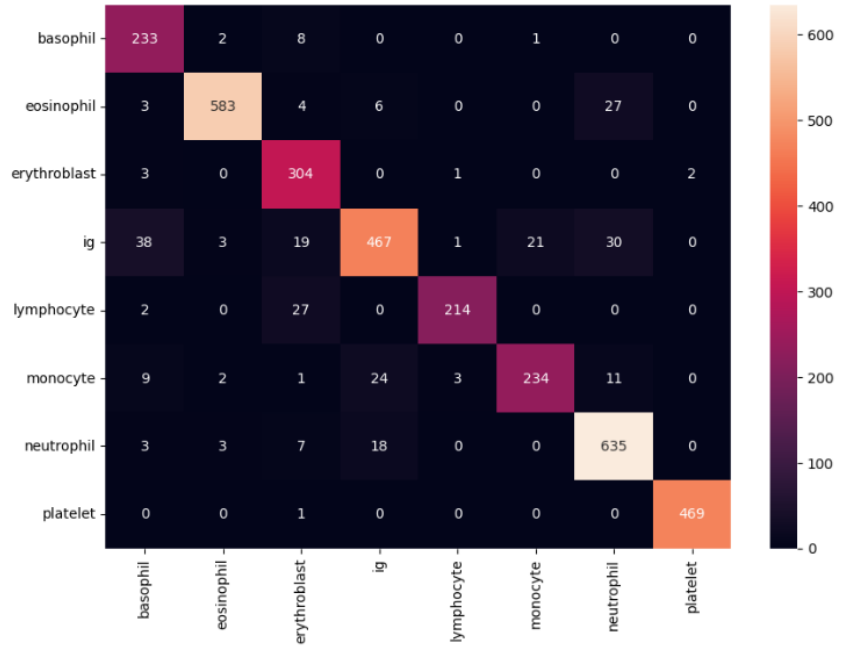

Figure 4.5: Confusion matrix of VGG16 model

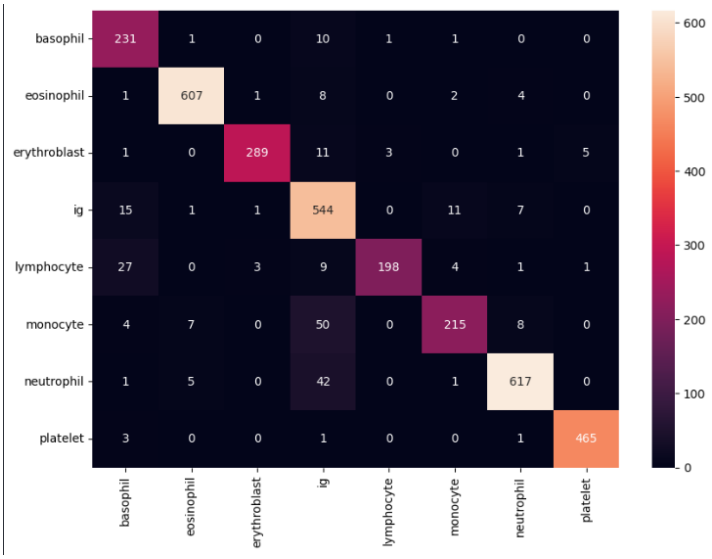

Figure 4.6: Confusion matrix of EfficientNetB3 model

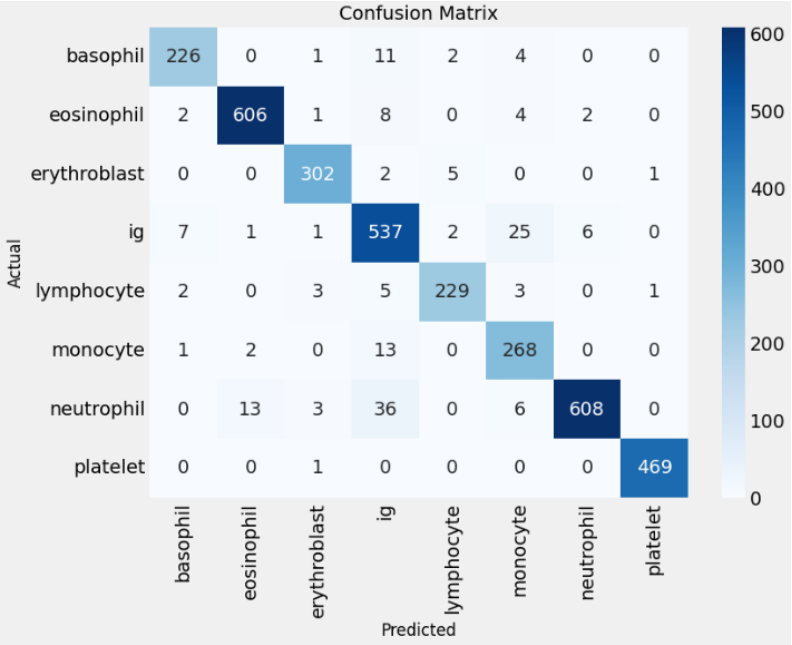

Figure 4.7: Confusion matrix of Hybrid model

4.3 Results and Discussion

4.3.1 Result Analysis

Table 4.3: MobileNetV2 model performance

Class	precision	recall	F1-score
basophil	0.91	0.91	0.91
eosinophil	0.97	0.97	0.97
erythroblast	0.99	0.92	0.95
immature granulocytes	0.93	0.79	0.85
lymphocyte	0.90	0.96	0.93
monocyte	0.82	0.86	0.84
neutrophil	0.88	0.97	0.92
platelet	0.98	1.00	0.99
macro avg	0.92	0.92	0.92
weighted avg	0.93	0.92	0.92

According to Table 4.3, The MobileNetV2 model classified eight kinds of blood cells with an overall accuracy of 92%. Each class's precision, recall, and F1-score metrics show great performance; eosinophils and platelets have very high precision and recall (0.97 for both) and 0.98 and 1.00 for both, respectively, leading to strong F1-scores of 0.97 and 0.99. With an accuracy of 0.99 and a recall of 0.92, the erythroblast class likewise did well, achieving an F1 score of 0.95. F1 scores of 0.91, 0.93, and 0.92 were attained by other classes, including neutrophils, lymphocytes, and basophils, which demonstrated robust and balanced metrics. Due to lower recall values (0.79 for immature granulocytes and 0.86 for monocyte), the immature granulocytes and monocyte classes performed marginally worse, with F1-scores of 0.85 and 0.84, respectively. The model successfully managed class distribution, as evidenced by the weighted average F1-score of 0.92 and the macro average F1-score of 0.92, which showed balanced performance across all classes. The model shows good generalization to the dataset with a loss of 0.25, which is a comparatively low error rate throughout training and testing. Although the recall for the immature granulocytes and monocyte classes might be improved to increase the model's efficacy, overall, the MobileNetV2 model provides dependable classification performance.

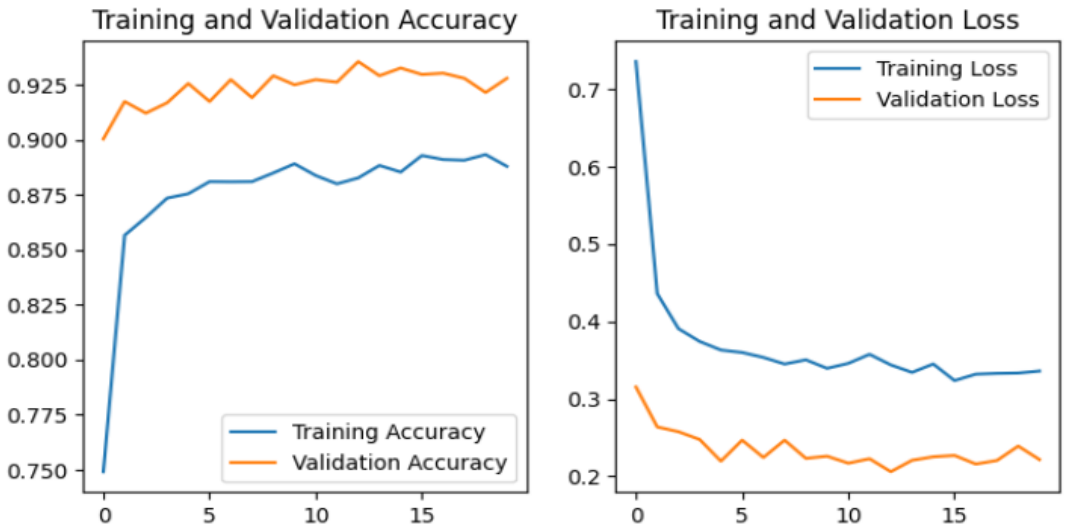

Figure 4.8: MobileNetV2 accuracy and loss graph

Table 4.4: Inception V3 Model Performance

Class	precision	recall	F1-score
basophil	0.81	0.87	0.84
eosinophil	0.92	0.97	0.94
erythroblast	0.84	0.93	0.88
immature granulocytes	0.85	0.65	0.74
lymphocyte	0.90	0.93	0.91
monocyte	0.77	0.88	0.82
neutrophil	0.92	0.94	0.93
platelet	1.00	0.99	0.99
macro avg	0.88	0.89	0.88
weighted avg	0.89	0.89	0.89

According to Table 4.4, The InceptionV3 model's performance on the test dataset shows a loss of 0.88 and an overall accuracy of 89%, suggesting dependable classification across the eight blood cell classifications. The model performs well overall, with a weighted average accuracy, recall, and F1-score of 0.89. Class-specific analysis demonstrates the model's capacity to successfully differentiate between neutrophils (F1-score: 0.93, precision: 0.92, recall: 0.94) and eosinophils (F1-score: 0.94, precision: 0.92, recall: 0.97). The model's remarkable ability to identify the platelet class with few mistakes was demonstrated by the platelet class's greatest accuracy (1.00) and F1-score of 0.99. With an F1-score of 0.91, lymphocytes also did well, with balanced precision (0.90) and recall (0.93). In a similar vein, the basophil class performed well, obtaining an F1-score of 0.84 backed by a recall of 0.87, demonstrating the model's dependability in class detection. But some classes performed worse than others. A decreased recall of 0.65 affected the immature granulocytes class's F1-score of 0.74, indicating difficulties reliably recognizing this class. With an F1-score of 0.82 and recall (0.88) higher than precision (0.77), monocytes demonstrated the possibility of an accuracy increase for this class. Although the macro-average F1-score of 0.88 indicates that performance across all classes is generally balanced, more fine-tuning might increase accuracy for monocytes and recall for lagging classes like immature granulocytes. Notwithstanding these drawbacks, the InceptionV3 model remains a dependable option for peripheral blood cell image analysis due to its strong classification skills and efficient feature extraction.

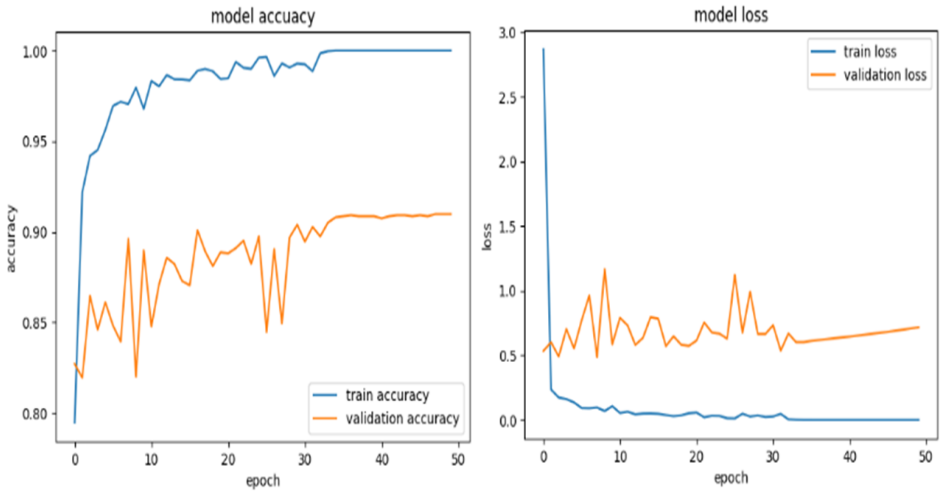

Figure 4.9: Inception V3 model accuracy and loss graph

Table 4.5: ResNet50 Model Performance

Class	precision	recall	F1-score
basophil	0.82	0.90	0.86
eosinophil	0.93	0.98	0.95
erythroblast	0.88	0.94	0.91
immature granulocytes	0.82	0.66	0.73
lymphocyte	0.91	0.94	0.92
monocyte	0.70	0.90	0.79
neutrophil	0.94	0.88	0.91
platelet	1.00	0.99	1.00
macro avg	0.88	0.90	0.88
weighted avg	0.89	0.89	0.89

According to Table 4.5, The ResNet50 model demonstrated dependable performance in categorizing peripheral blood smear pictures across eight classes, with an overall accuracy of 89% with a loss of 0.42. Eosinophil (F1-score: 0.95) and platelet (F1-score: 1.00) were high-performing classes with almost flawless accuracy and recall levels. Balanced F1 scores above 0.90 were attained by other well-classified groups, including neutrophils, lymphocytes, and erythroblasts. However, because of difficulties with memory and accuracy, respectively, immature granulocytes (F1-score: 0.73) and monocytes (F1-score: 0.79) performed worse. Consistent performance throughout the dataset is indicated by the weighted-average F1-score of 0.89 and the macro-average F1-score of 0.88. Resolving class imbalance and improving performance for underrepresented groups like immature granulocytes and monocytes might further increase ResNet50's usefulness for hematological diagnoses, even though it excels at feature extraction for dominant classes.

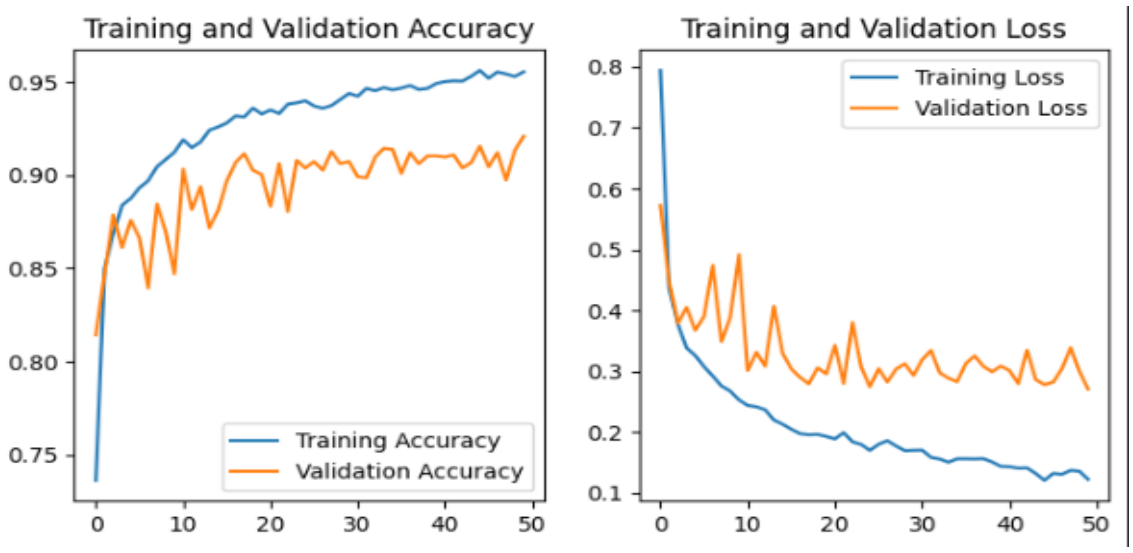

Figure 4.10: ResNet50 accuracy and loss graph

Table 4.6: ResNet101 V2 Model Performance

Class	precision	recall	F1-score
basophil	0.82	0.95	0.88
eosinophil	0.96	0.97	0.97
erythroblast	0.36	0.92	0.94
immature granulocytes	0.82	0.91	0.86
lymphocyte	0.92	0.85	0.88
monocyte	0.93	0.77	0.85
neutrophil	0.96	0.91	0.94
platelet	0.98	0.99	0.98
macro avg	0.91	0.91	0.91
weighted avg	0.92	0.92	0.92

According to Table 4.6, The ResNet101V2 model performed well in categorizing peripheral blood smear pictures, with an overall accuracy of 92% with a loss of 0.37. With near-perfect accuracy and recall values, the model performed exceptionally well in high-performing classes including platelets (F1-score: 0.98), and eosinophils (F1-score: 0.97). With F1-scores of 0.94, erythroblast and neutrophil both showed strong results, demonstrating the model's capacity to manage visually dissimilar groups. Classes like monocytes (F1-score: 0.85) and immature granulocytes (F1-score: 0.86) showed moderate performance. immature granulocytes had balanced precision and memory, but the monocyte's recall of 0.77 suggests difficulties in detecting all true occurrences. A somewhat poorer recall of 0.85 contributed to the lymphocyte class's F1-score of 0.88, indicating room for improvement in these areas. With evenly distributed contributions, the weighted-average F1-score of 0.92 and the macro-average F1-score of 0.91 demonstrate steady performance across all classes. This helps to understand that ResNet101V2 contains a great potential for feature extraction due to its high accuracy and precision. Its categorization balance may be better, nonetheless, if more improvements are done on the structurally underrepresented or challenging sub-groups such as monocytes and lymphocytes. Thus ResNet101V2 is perfect for classification of hematological images because it implies computer resource saving, very high accuracy, and feature extraction.

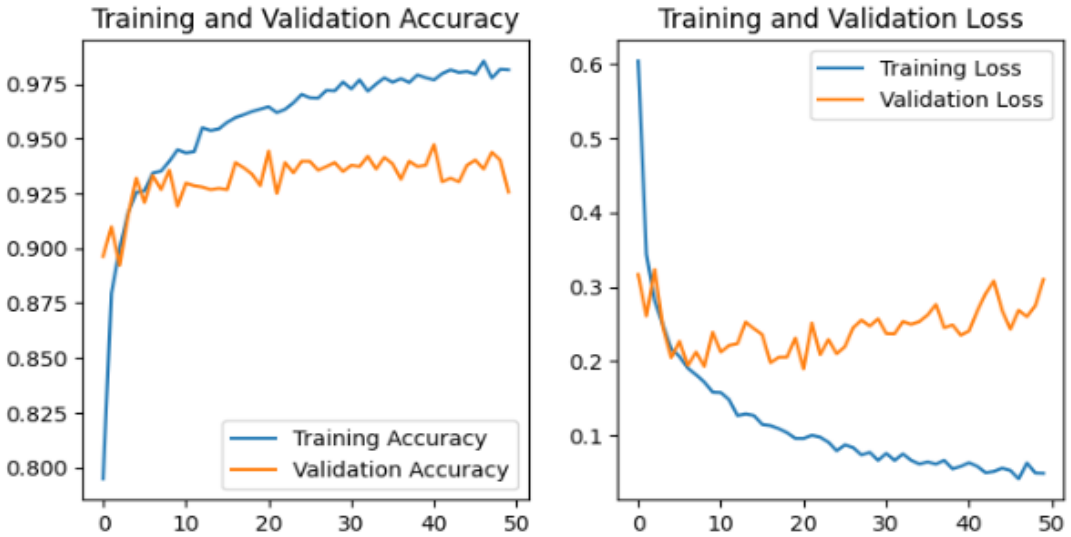

Figure 4.11: ResNet101V2 accuracy and loss graph

Table 4.7: VGG16 Model Performance

Class	precision	recall	F1-score
basophil	0.91	0.91	0.91
eosinophil	0.97	0.97	0.97
erythroblast	0.99	0.92	0.95
immature granulocytes	0.93	0.79	0.85
lymphocyte	0.90	0.96	0.93
monocyte	0.82	0.86	0.84
neutrophil	0.88	0.97	0.92
platelet	0.98	1.00	0.99
macro avg	0.92	0.92	0.92
weighted avg	0.93	0.92	0.92

From Table 4.7, it can be observed that the VGG16 received a good classification result with an accuracy of 92% and lost 0.27. Perfect accuracy, recall, and F1 scores of 1.00 with platelets, an F1 score of 0.96 with eosinophils had balanced accuracy and recall. However, neutrophils as well as lymphocytes, scored impressive F1's of 0.93. Erythroblast (F1-score: 0.89), and basophil (F1-score: 0.87), showed moderate performance, with sporadic false positives and minor imbalances in accuracy and recall. Recall and accuracy were lower for lower-performing classes, such as monocytes (F1-score: 0.87) and immature granulocytes (F1-score: 0.85). All classes are consistently and fairly classified, as evidenced by the weighted-average F1-score of 0.92 and the macro-average F1-score of 0.91. VGG16 performs consistently overall, outperforming dominant classes while having space for growth in underrepresented ones.

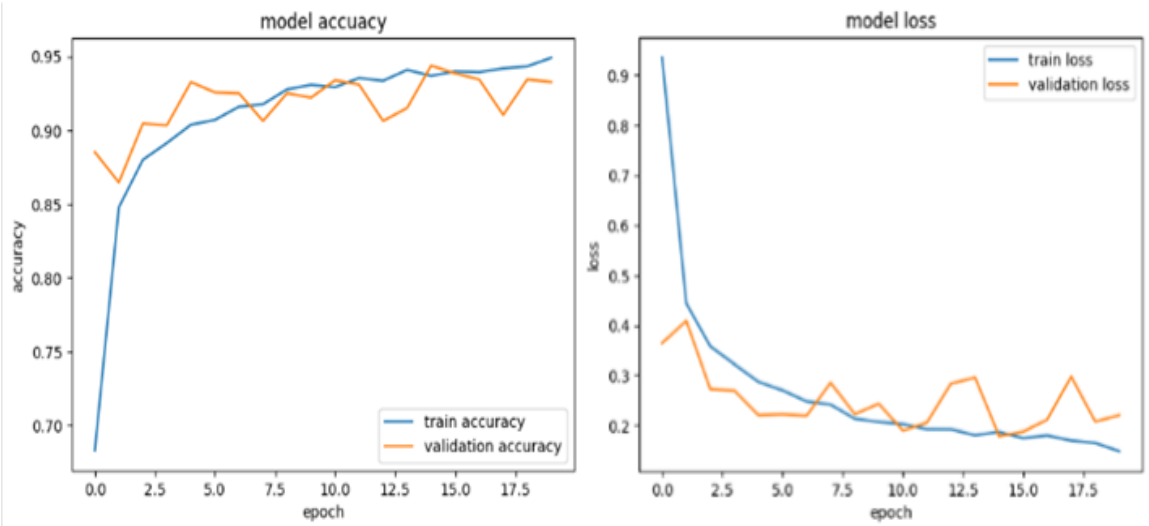

Figure 4.12: VGG16 accuracy and loss graph

Table 4.8: EfficientNetB3 Model Performance

Class	precision	recall	F1-score
basophil	0.82	0.95	0.88
eosinophil	0.98	0.97	0.98
erythroblast	0.98	0.93	0.96
immature granulocytes	0.81	0.94	0.87
lymphocyte	0.98	0.81	0.89
monocyte	0.92	0.76	0.83
neutrophil	0.97	0.93	0.95
platelet	0.99	0.99	0.99
macro avg	0.93	0.91	0.92
weighted avg	0.93	0.93	0.93

According to Table 4.8, The model performed well in categorizing peripheral blood smear pictures, achieving an astounding 93% accuracy with a low loss of 0.23. High-performing classes with balanced accuracy and recall, such as neutrophils, erythroblasts, platelets, and eosinophils, had F1 scores between 0.95 and 0.99. These outcomes show how reliable the model is in recognizing different and well-defined cell types. Basophil (F1-score: 0.88) and immature granulocytes (F1-score: 0.87), which showed moderate performance, had good recall values but somewhat poorer accuracy, suggesting sporadic false positives. The lymphocyte (F1-score: 0.89) and monocyte (F1-score: 0.83) classes performed poorly, with recall and accuracy issues resulting in missing or inaccurate predictions. Consistent performance across all classes is shown in the weighted-average F1-score of 0.93 and the macro-average F1-score of 0.92. The model exhibits outstanding generalization and dependability, with the potential for enhancing the categorization of difficult groups such as monocytes and lymphocytes using sophisticated data augmentation or fine-tuning methods.

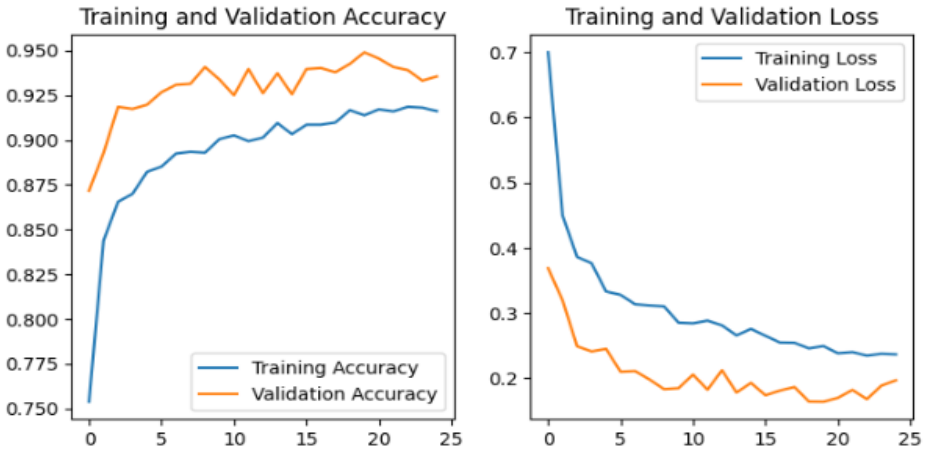

Figure 4.13: EfficientNetB3 accuracy and loss graph

Table 4.9: Hybrid Model Performance

Class	precision	recall	F1-score
basophil	0.95	0.93	0.94
eosinophil	0.97	0.97	0.97
erythroblast	0.97	0.97	0.97
immature granulocytes	0.88	0.93	0.90
lymphocyte	0.96	0.94	0.95
monocyte	0.86	0.94	0.90
neutrophil	0.99	0.91	0.95
platelet	1.00	1.00	1.00
macro avg	0.95	0.95	0.95
weighted avg	0.95	0.95	0.95

Display on Table 4.9, By integrating Mobilenetv2 with EfficientNetb3 the Hybrid Model in the current study was able to predict the type of blood cells, with a near-accurate prediction rate of 95%, and a low loss ratio of 0.15. Based on F1 score, eosinophil, erythroblast, and neutrophil showed high classification with F1 score rating of 0.97 - 1.000, implying its stability and reliable, while platelets yielded an accuracy, recall, and F1 score of 1.000. Because of better generalization abilities the hybrid model demonstrated moderate improvement in hard classes such as immature granulocytes, where F1-score was 0.90 and monocytes where F1-score was equal 0,90. Production cell classification was presented with the highest overall competency, TC50 = 90%, as well as monocyte F1-score = 0,90. The results on lymphocytes were also reasonable with slightly higher accuracy than recall, and the given F1-score of 0.95. The highlighted results are the course level WA and macro-average F1-scores of 0.95 for all the courses. This outcome confirms the understood advantage of presented hybrid approach, which combines high accuracy feature extraction of EfficientNetB3 with the lightweight MobileNetV2 baseline. The presented approach proves to be better than models individually and has potential for further development to provide efficient classification of blood cells.

Figure 4.14: Hybrid Model accuracy and loss graph

4.3.2 Discussion

In order to categorize peripheral blood smear pictures into eight distinct blood cell types, we tested the effectiveness of five pre-trained deep learning models in this study: MobileNetV2, ResNet50, ResNet101V2, InceptionV3, and VGG16. Additionally, we tested a Hybrid Model that combines MobileNetV2 and EfficientNetB3. With an overall accuracy of 95%, the Hybrid Model fared better than any single model. It showed greater precision, recall, and F1-scores in every class, particularly for difficult categories like platelets and eosinophils, which received nearly flawless scores. ResNet101V2 had a slightly larger loss of 0.37 but attained 92% accuracy. Although it offered superior recall and precision for some classes, such as platelets and eosinophils, its practical use in real-time applications was constrained by its high processing cost and longer training period. VGG16 did quite well, however its precision and recall for immature granulocytes and monocytes were lower (92% accuracy, 0.27 loss). With 89% accuracy and greater loss values (0.42 and 0.88, respectively), InceptionV3 and ResNet50 performed the worst. They needed more tuning because they struggled with immature granulocytes and monocytes but performed well for bigger classes like neutrophils and platelets. In summary, the Hybrid Model showed the best performance balance and efficiency. Its high precision and scalability make it perfect for real-world applications, particularly those with restricted resources. Recall problems for underperforming courses may be the main focus of future enhancements.

4.4 Summary

This chapter discussed the implementation and evaluation of deep learning techniques for the automated classification of peripheral blood smear images into eight blood cell types. Google Colab as an environment was set for the model testing and training using GPU to ensure proper testing. A dataset of 17,092 labeled blood smear pictures was used in improving the six pre-trained models, which include, MobileNetV2, ResNet50, ResNet101V2, InceptionV3, VGG16, and a Hybrid Model that uses MobileNetV2 and EfficientNetB3. Performance of each model was measured using accuracy, precision, recall, and F1-score. The Hybrid Model had a maximum accuracy of 95% with a great class–wise performance especially in platelets and eosinophils. It reaches a high accuracy of 92% and has proved to be very efficient making the MobileNetV2 suitable for real-time applications in several low-resource environments. Despite the fact that other structures had higher computing complexity and class-specific challenges, like ResNet50 and VGG16 there were satisfactory results with attention to underrepresented categories, including immature granulocytes and monocytes. The results obtained in the study are evidence of the possibility of applying deep learning models for automated interpretation of peripheral blood smears. However, based on its starvation accuracy and computational speed, it is discovered that the Hybrid Model excels as the most balanced. It makes it ideal for practical use especially those that can't afford to invest in complex models.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

5.1.1 Software Standards

To ensure that the study adhered to internationally established conventions for software development, the study followed industry standard norms to ensure the proper functioning and more importantly replicability of results. The labeled dataset used in this research was sourced from Kaggle which is a reliable data access and management platform. For faster computation and easy interaction with the Python-based libraries, Google Colab has been used to train and evaluate the models. On Windows 11, there was no problem related to the development and test environment as well as coding jobs. This allowed the development a solid basis for the study as well as providing reliable sources for performing the literature analysis and citation of the studies.

5.1.2 Hardware Standards

Care was taken to ensure that the right hardware was used for this project with issues of performance and accessibility in mind. This particular device was LAPTOP-37ILUPFA with an AMD Ryzen 3 3250U clocked at 2.60GHz having Radeon Graphics. The laptop had 512 GB SSD for the storage function and data processing, also, the laptop was endowed with 8 GB RAM for the coded execution. Maintaining a low cost and availability for most of the potential users of the platform it ensured the adequate amount of computing power for the preprocessing, training, and validation of the models.

5.1.3 Communication Standards

For the duration of the project proper proven communication lines were maintained to ensure good management and collaboration. Data along with code files and documentation files were sourced and stored at Google Workspace (documents, spreadsheets, drive). Through Zoom or Google Meet, daily or weekly meetings were conducted to give actuality and debates. Instant communication tools such as telegram, were used so that members can communicate effectively and efficiently in an instant and do what is expected of them. These communication standards were helpful in the implementation process and achievement of the project.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The proposed automated approach to sort peripheral blood smear pictures is a revolutionary contribution to the field of healthcare since it improves the diagnosis of hematological issues by increasing the speed and extent of their identification. Microscopic examination by naked eye is a lengthy process, requires special and precise expertise, and is capable of producing variability due to erroneous human effort and fatigue. With the help of the technology, this task is done far more quickly, and more efficiently and accurately, affecting the direct care of the patients and the results. This quick accurate determination enables early treatment that in critical cases, saves lives since therapy is well directed towards the disease in question particularly in leukemia, anemia and infection diseases majorly determined by blood cell count results. Also, this technology helps to reduce the number of highly qualified pathologists that is useful in directing professionals to other complicated cases. This automated technology ensures people in areas with limited doctors attain quality diagnostic services hence improving on the quality of healthcare they receive as a result of limited access to quality specialized doctors for their conditions. The capacity to classify eight different types of blood cell means that the progression of diseases can be more effectively monitored and, in turn, patient health and management is enhanced. Furthermore, the presence of this technology leads to the enhancement of operative procedures in real-time health care activity. It helps care providers deliver timely medical treatment by clearing bottlenecks in diagnostics, especially in centralized laboratories. This technique reduces variations in findings by providing a reliable tool for standard and systematic assessment for any applicants who may be undergoing a periodic check, for instance, chronic haematological diseases. Other than fulfilling needs of timely diagnostic necessities, the method aids advancements in medicine. Because of its capability to process large data sets that facilitate its use in research focused on understanding the illness processes and developing new treatments. In conclusion, the method given above enhances the quality of health care delivery, helps to increase the rate of healing and aims at helping humanity provide the fair battled access to the diagnostic equipment.

5.2.2 Impact on Society & Environment

This is perhaps the major strength of the method advocated here, more so in addressing issues of health related disparities in health care. Automated blood smear analysis offers the complicated diagnostic capabilities in a more tender or remote regions, helping to equalize the disparity between developed and developing nations' healthcare industries. The technology ensures that inequality in healthcare delivery is eradicated because the technology avails cloud options if not portable solutions ensuring that disadvantaged circumstances attending patients can access timely accurate results. Additionally, the method reduces the workload on the overburdened medical experts within the healthcare sector to focus only on cases, which require their skills at that particular stage. From the environmental perspective, one of the improvements is that wastes are minimized since most of the processes involve digital and automatic rather than manual and chemical.

Biomedical waste cost is an outcome of conventional systems due to concentration on consumables including but not limited to glass slides, chemical reagents, and several disposables. The suggested solution decreases the demand for such consumables by eliminating blood smear analysis as a traditional time-consuming activity while promoting greener laboratory processes. Also, the reduction of paper in capturing and reporting of the diagnostic information fosters an environmental friendly healthcare framework, and enhances the global sustainable agenda. As for model training and assessment, resources like Google Colab are being employed, which cuts down the energy intensity mostly associated with powerful local servers. Light weight models such as MobileNetV2 are computationally efficient and do not cause high energy consumption during deployment to the extent of making the whole system unsustainable especially when deployed in areas of low resource. These models could be possible next-generation diagnostic available from practitioners without relying on energy-hungry apparatus, and if placed in portable devices They decrease the overall medical carbon footprint. Therefore, in addition to providing the society with high quality diagnostics, the proposed method embraced reduction of wastes, energy consumption and utilization of conventional lab procedures when developing the algorithm. The general adoption of global healthcare may make a huge difference and make healthcare more sustainable across the globe as well as easier to access to all.

5.2.3 Ethical Aspects

There are certain ethical questions when AI is utilized in the medical diagnostics, and in this case these questions should be addressed so that it is possible to guarantee safe and sensible use of this tool. Bias and model explainability are subjects that possess two of the most basic norms for ethical AI. This is averted by the suggested solution where balanced datasets are employed and a variety of preprocessing techniques were used in order to make certain that all the blood cell types are fairly handled without prepossessing the problem of having very few data points of monocytes and immature granulocytes. It helps to exclude prejudicial issues that in term may prejudice the fate of some patient populations. Another ethical issue relate to patient's privacy and security of their information that is to be shared in a health facility. Medical data is private data; therefore they must be processed in compliance with the privacy acts such as GDPR and HIPAA. Frequently, several barriers are employed to ensure that unauthorised persons do not access patient data, and the suggested system ensures that the data is anonymised as the processing is being done. Transparency is also an imperative feature of such approaches in the context of AI-driven diagnostics. To ensure confidence in its decision making, the system employs XAI motivated procedures such as the Grad-CAM that gives a visual perception into the system's thinking. This ensures that the AI recommendations bring value addition to human experience and not the vice versa and allows doctors to cross check its outputs. The use of the technology is also an area of consideration of the ethical dilemmas. The concept behind the technology is to assist doctors, so pathologists are not to be replaced but to have supervisory and decision-making authority. This cooperative strategy takes care of issues of job replacement with concerns for proper implementation of AI tools within the operations of a healthcare organization. In addition, the system is very economical in terms of resources used and the model is developed such that it is

possible to implement it in any health facility regardless of the available resources meaning that the problem of inadequacy of resources to implement the system cannot worsen the problem of disparity. The approach recommended does so by addressing these ethical issues, in order to develop an ethical approach to the use of AI in medical diagnostics. It promoted equity, openness and responsibility way of using technology to ensure that the improvement of health care outcomes is not compromised with moral standards as well as public perception is considered.

5.2.4 Sustainability Plan

Hence, sustainability of the suggested system lies in the fact that it is: scalable; resource-efficient; and adaptable to changes that may arise in the delivery of health care. Due to this efficiency, MobileNetV2 and the Hybrid Model as light weight models can be applied in low resource settings such as mobile health clinics or in rural areas. This ensures that if ever the system will be fine tuned for a purpose of extending its coverage, even the excluded sectors of the society can be considered not requiring much infrastructural overhaul on the part of the utility. Additionally, since sustainability of the system also depends on the frequent updates and regular maintenance, cloud-based deployment add to its sustainability by ensuring that the system is always right and relevant due to continuous growth of the medical field. The integration with telemedicine platforms increases the accessibility of health care services in other areas since it creates the possibility to have a diagnostic function. This strategy reduces the amount of carbon that is emitted, as well as the amount of money spent on logistics, not only for patients to be taken to these specialist facilities but also makes the process of practice of health care logistics environmentally sustainable. The system strongly focuses on the means of modular architecture to ensure its future-proof longevity as well as easy integration with other devices and technologies. Operating cost reduction and environmental impacts' minimisation ensure that the system remains economically and ecologically sustainable. This way, the suggested method meets international goals for rational and impartial provision of healthcare and stewardship of our environment, and establishes the stable foundation necessary for modern diagnostics.

5.3 Project Management and Financial Analysis

In order that this investigation could be successfully carried out, sound financial management and effective administrative project management could not be overemphasized. To ensure that all the known compliance standards were met, costs of the entire project were effectively managed. To store data, a pen drive was bought which cost 1 thousand BDT and to photocopy the reports, 5 hundred BDT were spent. Furthermore, 1000 BDT was used for mobile data since they are needed to connect with the internet platform, databases and cloud services such as Google collaboration. The "others" group had other small expenses such as energy or printing materials. To minimize on costs for software, the sensitization project was able to use Google Colab for model training and Kaggle for datasets since they were free. Since most of the components like laptop was purchased the additional hardware was not incurred. The total money spent also reflects the cost-efficient approach to the economic resource management with

parallel quality capacity retention. This own financial assessment guarantees applicability and feasibility for similar studies in limited-resource scenarios by providing evidence that conducting technically sophisticated contexts of machine learning studies is possible with relatively limited funding.

Figure 5.1: Project Management

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

There were several challenging problems during this study, for example how to address the picture fluctuation, how to solve the class imbalance problem, and above all how to achieve the best accuracy and computationally efficient study. In some cases, where resources were restricted, lighter models were used in order to assure the adequacy of the results. Also, ethical questions such as privacy of data and Vị unbiased forecast were discussed. As seen in Table 5.1, these difficulties were addressed using complicated preprocessing, model selection, and comprehensive evaluation.

Table 5.1: Mapping with complex problem-solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stakeholder Involvement	EP7 Interdependence
✓	N/A	N/A	✓	N/A	N/A	✓

EP1: Dept of Knowledge

Specifically, the project requires knowledge of hematological diagnostics and image processing in addition to deep learning as the multi-disciplinary abilities. Such a data processing approach using advanced pre-trained Hybrid Model, EfficientNetB3, and MobileNetV2 models proves the profound knowledge of such fields.

EP4: Familiarity of Issues

Concerning the objectivity of the issues addressed in the initiative, it was focused on the issues of cell overlap, staining variability, and class imbalance in medical imaging. These distortions were reduced by applying Gaussian filtering and Laplacian sharpening preprocessing techniques.

EP7: Interdependence

To ensure dependency, the project included data preprocessing, model fit, and model performance steps, which confirms covariate dependency.

Mapping with Knowledge Profile for EP1

The development method of the blood smear categorization highlighted the challenges by using advanced engineering domains including; machine learning, image processing and medical diagnosis. Table 5.2 shows these regions in relation to the project to identify their transdisciplinary skills used across the different phases.

Table 5.2: Mapping with Knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓		✓

K3: Engineering Fundamentals
An automated system for categorizing blood smear samples is being designed through the application of what is essentially basic engineering whereby computational modeling, data preprocessing as well as optimal systems designs are featured. These basic approaches enabled the achievement of accurate and reliable over categorization study results.

K4: Specialist Knowledge
Advanced knowledge of both artificial intelligence and medical imaging is provided by the application of deep learning methods including pre-trained models MobileNetV2, EfficientNetB3, and a hybrid model to hematological diagnosis.

K5: Engineering Design
And in order to both get proximal to the actual phenomenon and to compute at speed, leans heavily both on good engineering design, light weight architectures, preconditioning, and choice of models.

K8: Research Literature
In this project, critical literature review is expected, where the current approaches and results are compared for the detection of the gaps and then to ensure the relevance of the proposed solution. The work reaffirms this alignment with literature and supports the development of the system and its capacity to contribute to the field.

5.4.2 Engineering Activities

Several elements of the engineering process were involved in the endeavor of the study including data preprocessing, model development, model evaluation and outcome evaluation. Table 5.3 aligns these tasks to this and shows how well they fit the technical objectives while also reflecting on the project's methodical nature.

Table 5.3: Mapping with complex engineering activities.

EA1 Range of re-resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓			✓	✓

EA1: Range of resources
The following resources were used in the course of implementing the project: pretrained models like MobileNetV2, EfficientNetB3, Hybrid Model, Kaggle for data sourcing and Google Colab for model training with good amounts of GPUs. These resources ensured that all the categorization processes presented in figure one were done appropriately for implementation and scalability.

EA4: Consequences for society and environment

This section dealt with the impact that the implementation of the strategy will have on the society and the environment. It is therefore in the best interest of society that the system can classify blood smears independently to reduce time and increase efficiency of correct diagnosis. In this case, the digital aspect of the solution plays a part in sustainability of diagnostics by reducing on the amount of consumables used such as slides and chemical reagents.

EA5: Familiarity

Some of the common problems associated with medical imaging such as class imbalance, staining heterogeneity and regions of overlapping cells were handled by this approach. These well-known problems have been solved with an improved model selection and training, as well as with preprocessing methods such as Gaussian filtering and Laplacian sharpening.

5.5 Summary

Thus, the following engineering requirements were followed in developing an efficient automated blood smear categorization system. The software standards included for literature review was Google Scholar and Google Colab for model training with GPU support and dataset was collected from Kaggle. The laptop of 512 GB SSD and 8 GB RAM made up the gear in order to get the desired computations. Collaborative platforms such as Google and workspace as well as zooms were used to enhance on communication. Other challenging questions were answered such as how to manage the variation of pictures, how to minimize class imbalance and how to balance between computer speed and model accuracy. In order to improve the quality of the overall picture, two techniques were performed; Gaussian filtering and Laplacian sharpening. As per the need of the datasets such pre trained models like MobileNetV2, ResNet50 and the Hybrid Model were selected to get high accurate results but at the same time minimizing the computational cost. Activities given are data gathering and data preparation, model development and training and a scoring on F1, accuracy, precision, recall. Using MobileNetV2 and EfficientNetB3 the Hybrid Model contributed the best results to achieve the peak performance the model aimed for. Therefore, the experiment gratifyingly solved the design problems, and passed engineering specifications while designing an efficient and accurate automated blood smear categorization system for practical implementation in the medical scenario.

Chapter 6

Conclusion

6.1 Summary

This work applied deep learning methods in classification of eight types of blood cells: The need for overcoming the difficulties in the image processing of peripheral blood smear picture is fulfilled by the classification of the cells into basophil, eosinophil, erythroblast, immature granulocytes, lymphocyte, monocyte, neutrophil, and platelet. The total 17192 images were used in the current study after pre processing in which the given images were further divided into training set, validation set and the test set. Accuracy, precision, recall, and F1-score were used to assess the implementation of Six pre-trained deep learning models: , Mobile Net v2, ResNet 50, ResNet 101 v2, Inception v3, Efficient Net b3, and VGG16. We first combined MobileNetV2 and EfficientNetB3 to form a new Efficient-MobileNetV2, which we enhanced and evaluated. The Hybrid model demonstrated the highest level of efficiency and equilibrium, having an accuracy of 95%, and a loss of only 0.15. It also yielded good generalization and low computational load. The study emphasizes how automated diagnostic technologies have the potential to revolutionize hematological diagnostics by increasing their speed, accuracy, and scalability for a range of healthcare settings.

6.2 Limitation

There are a few significant issues that need to be resolved even if the automated blood smear categorization method has shown encouraging results. One major problem with the dataset is the class imbalance. The data showed the underrepresentation of several blood cell types, especially immature granulocytes, and monocytes, which hindered the model's ability to correctly categorize these cells. Prediction mistakes were the result of these classes' worse recall and accuracy. Generalization is another difficulty. Even while the models did well on the training dataset, they might not do as well on fresh, real-world data. These variations consist in differences in picture quality, staining techniques or image noise which cause the model to poorly perform on unseen data. Nonetheless, for practical usage, the expansion of the model's applicability to various scenarios and types of data is needed further. What we see as a disadvantage of some of the models like ResNet101V2 or VGG16 is that their training and running time is quite high. However, for more specific real-time purposes including areas of lower processing capacity such as mobile clinics or rural hospitals, these models may not be effective because of their high processing time and compute complexity. DDN models, such as MobileNetV2 and the others listed in this paper, are less computationally heavy but inaccuracies might be found in them. Last but not least, the quality and the variety claims of the dataset used for training clearly affect its performance. Despite the fact the study had a large dataset, the authors were unlikely to exhaust all possible variations in the pictures of blood

smears. For real-world scenarios with poorer image quality, the model can get it wrong when identifying blood cells without exposure to a variety of samples.

6.3 Future Work

Future research might look at a number of issues to enhance the blood smear categorization system and it's usefulness or effectiveness. Eradicating class division should be deemed to be one of the most significant goals. The model has some errors in identifying less distinctive cell types including immature granulocytes and monocytes;the problem could be solved by applying data augmentation, in other words, creating additional data for underrepresented classes, or by using synthetic data generation. An additional concept for future research is to randomly obtain more diverse blood smear pictures so that they contain more pictures of diverse quality and with different staining procedures or background noise so that the approach can generalise about diverse pictures with reasonable levels of accuracy. A larger sample size will help make useful changes in actual practice environment and also increase robustness of the model in a way that has not been considered in this paper. Meantime, using the technology in real-time applications also demands reducing the computing cost. Future work may be dedicated to enhancing the models with the help of practices of pruning, model compression, or simply more lightweight ones. These techniques will enhance the efficiency of these models in terms of time and energy so vital in any environment that lacks adequate resources to undertake these exercises. Moreover, it may be integrated with telemedicine systems, which would allow the specialists to have the possibility to use the blood smear categorization tool through the internet connection. This shall improve the health care services availability in areas of scarcity or difficult reach through providing quick aid in pathology wherever qualified experts in pathology may be scarce. Lastly, clinical testing as well as practice implementation are closely related and other essential subsequent steps. Real healthcare situations should be utilised for practical testing on how well and in what ways they work and are easy to use after tuning these models. It will also help optimize before large-scale implementation and help find potential acceptance challenges, e.g., integration with current healthcare processes and usage experience.

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DEEP LEARNING APPROACHES FOR ANALYZING MICROSCOPIC PERIPHERAL BLOOD CELL IMAGES

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