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A Comparative Analysis of Machine Learning and Deep Learning Techniques for Classifying White Blood Cells

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ABSTRACT

Examining the different types of white blood cells (WBCs) is a key diagnostic tool for leukemia and infections. While many machine learning (ML) and deep learning (DL) approaches have been applied, prior works often lack clarity on computational processes and dataset details. This study provides a comprehensive comparative analysis between ML methods (SVM, KNN, ANN, Decision Trees) and advanced DL architectures (CNN, ResNet50, DenseNet121). The novelty of this work lies in presenting not only accuracy comparisons but also explicit computational equations, training configurations, and dataset handling strategies. Experiments were conducted on publicly available datasets (BCCD and Kaggle WBC datasets) using TensorFlow on GPU-enabled environments. Results demonstrate that DenseNet121 achieves the highest accuracy (98.84 %) on BCCD dataset, with superior generalization, outperforming traditional ML and basic CNNs. This study highlights the impact of transfer learning, augmentation, and computational efficiency, and offers a pathway for explainable AI integration in hematological diagnostics.Unlike existing surveys, this work details computational steps, training configurations, and highlights gaps for future development.

Keywords: White Blood Cell (WBC) classification, Machine Learning (ML), Deep Learning (DL), Convolutional Neural Network (CNN), Medical Image Analysis (MIA). AI in Healthcare.

I. INTRODUCTION

The immune system helps us to protect from illness and infection, andWhite blood cells (WBCs) are essential for a healthy human immune system. Detection and classification with accuracy of WBCs are necessary in the timely diagnose medical conditions such as leukemia, HIV, and other immunity-based disorders from the blood smear images. Historically, hematologists had to peruse through manually screened blood smears which was a painstaking and errantful process. In order to overcome these drawbacks, researchers have worked upondistinct machine learningand deep learning modelsto classify the White Blood Cells (WBCs) [1].

In recent years, WBC classification has gained increasing research attention due to its role in the timely detection of hematological disorders including leukemia, HIV, and bacterial infections. Recent studies [1][2] have shown that while traditional ML models achieve good results, their reliance on handcrafted features limits scalability. Deep learning models, with automated feature extraction, have significantly improved accuracy but face challenges in terms of data availability and computational costs. This study addresses these gaps by providing detailed explanations of ML and DL computation methods, highlighting dataset processing pipelines, and analyzing comparative results. The primary contributions of this work include: (i) a comparative analysis of ML vs DL with equations, (ii) explicit description of dataset usage, (iii) simulation and training details, and (iv) future research directions involving hybrid and explainable AI approaches.

As an example, the last years we have seen a strong transition from classical ML models to more sophisticated DL approaches for WBC classification. This paper presents a comparative analysis of these two categories of techniques, examining their accuracy, dataset requirements, and implementation challenges [2].

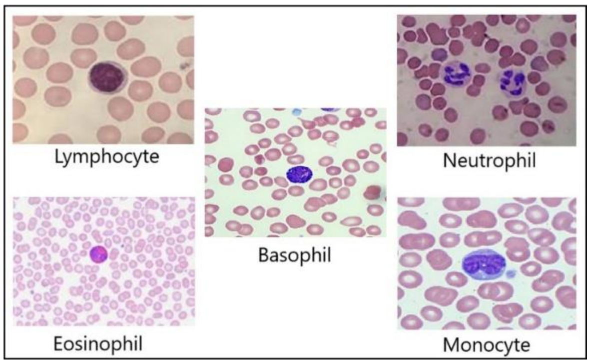

Fig 1: WBC types

II. MACHINE LEARNING MODELS FOR WBC CLASSIFICATION

2.1 An Outline of Machine Learning Models

Among WBC categorization techniques, machine learning (ML) became a popular methodology since the early days of medical image analysis. Usually, these methods are based on expert-engineered features extraction using image characteristics of blood smear images — shape, size, texture or color. After extracting the features, Decision Trees (DT), Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), and

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Support Vector Machines (SVM) classifiers were trained [2][3].

TABLE 1
POPULAR ML MODELS USED IN WBC CLASSIFICATION WITH ACCURACIES

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dataset Size
Support Vector Machine (SVM) [4]	98.60	96.20	98.50	Medium
Decision Tree (DT)	92.20	90.10	93.50	Small(UCI ML Dataset-500images)
K-Nearest Neighbors (K-NN) [5]	98.60	97.10	97.90	Medium
Naive Bayes	80.88	79.30	81.10	Small (BCCD-364 images)
Artificial Neural Network (ANN) [6]	94.20	99.40	99.18	Large (LISC-12500 images)

2.2 Feature Extraction in Machine Learning

The performance and outcomes of machine learning (ML) approaches in WBC classification heavily depends on how much qualitative features are extracted. Handcrafted features, including morphological and texture-based features, are critical to ensuring that the classifier can accurately differentiate between different types of WBCs. For example, feature cell area, perimeter, eccentricity and roundness have been reported to be useful for a better performance of SVM and KNN classifiers [7].

2.3 Popular Machine Learning Models

Support-Vector Machines (SVM): It is a considered as popular method for classifying WBCs since it can work with high-dimensional data and get very accurate results. Studies have shown that SVM models can achieve accuracies as high as 98.6% when applied to WBC classification using medium-sized datasets [8].

Decision Trees (DT): Decision Trees offer a simpler, interpretable model for WBC classification. While they generally have lower accuracy compared to SVM, they are useful for smaller datasets and provide insights into the decision-making process.

K-Nearest Neighbors (KNN): KNN has been effective in WBC classification, particularly for medium-sized datasets, achieving accuracies of up to 98.6%. To avoid the overfitting, hyperparameters like the number of neighbors (K) need to be carefully tuned. [9]

Artificial Neural Networks (ANN): ANN models, though an earlier form of deep learning, have been used in WBC classification with moderate success. Their accuracy improves with larger datasets, as seen in studies where ANN achieved 94.2% accuracy [10].

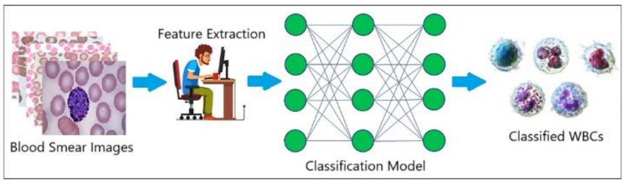

Fig 2: Machine learning workflow for WBC classification

III. DEEP LEARNING MODELS FOR WBC CLASSIFICATION

3.1 Introduction to Deep Learning

Last few years, Convolutional Neural Networks (CNNs) are anticipated top-notchtechniques based on popular choice for White Blood Cells (WBCs) classificationtasks. Deep learning models have the feature of automatic feature extraction and hence do not require handcrafted ones like the traditional ML models. Instead, they are designed to automatically learn features from the raw input images through multiple layers of convolutional filters [11].

3.2 Convolutional Neural Networks (CNN)

For WBCs categorization that involve classifying the medical images, CNNs found the most popular approach of deep learning architecture. They have shown better performance because they can learn hierarchical feature representations. Numerous CNN architectures, including ResNet, AlexNet, and DenseNet, are used for WBC classification, attaining accuracies surpassing 99.00% [12].

TABLE 2
COMPARISION OF CNN-BASED ARCHITECTURES FOR WBC CLASSIFICATION WITH RESPECTIVE PERFORMANCE MATRICS

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Dataset Size
CNN (AlexNet) [13]	96.30	98.85	99.61	Medium (Private- 9,069 synthetic images)
CNN (ResNet50) [14]	96.20	95.80	95.75	Small (ALL IDB2-260 images)
DenseNet121 [15]	98.84	98.85	99.61	Large(Kaggle-12,444 images)
Hybrid CNN (VGG, ResNet and Inception) [16]	92.66	95.53	85.92	Large (ISBI 2019-10691 images)

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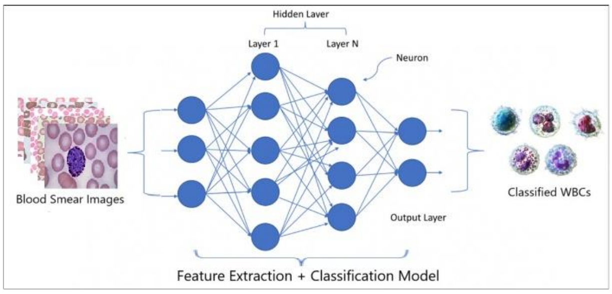

Fig 3: Visualization of a CNN architecture used for WBC classification.

3.3 Data Augmentation and Transfer Learning

Data augmentation,in deep learning, is often used to make the dataset bigger by changing the images in ways like rotating, flipping, and scaling them. This method helps CNN models work better in general, especially when there isn't much data to work with. Some fine-tuned models lie in transfer learning which are pre-trained on WBC datasets, has been proven to greatly enhance classification performance, making huge datasets less necessary.

3.4 Other Deep Learning Models

Recurrent Neural Networks (RNN) and Generative Adversarial Network (GANs) along with Long Short-term Memory (LSTM) networks are some other innovative deep learning architectures. These architectures were also explored for classification of the WBC. The essential property of these models is the ability to improve classification accuracy by exploiting temporal and sequential dependencies in images data [17].

TABLE 3
DLMODELS PERFORMANCE WITH ACCURACY BASED ON DATASET FOR WBC CLASSIFICATION

Model	Accuracy (%)	Data-set Size
RNN + CNN [18]	95.89	Medium(Kaggle + BCCD)
LSTM	95.89	Small(BCCD)
GAN + CNN [19]	99.90	Large(6562 real WBC images)

IV. COMPARATIVE EXAMINATION OD DEEP LEARNING AND MACHINE LEARNING METHODOLOGIES

4.1 Performance Comparison

While traditional ML methods such as SVM and KNN have achieved high accuracy in WBC classification, they are limited by their reliance on handcrafted features and the size of the dataset. In contrast, deep learning models, particularly CNNs, have demonstrated superior performance, especially when applied to large datasets. Deep learning methods can automatically learn hierarchical features, making them more robust and generalizable than traditional ML models [20].

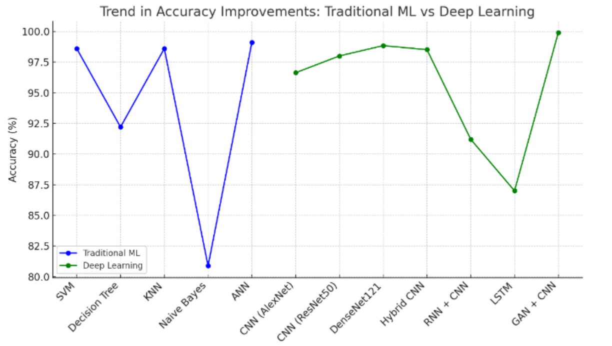

Fig 4: Trend in accuracy improvement from traditional ML to DL approaches

It clearly illustrates that while some ML models (like ANN, SVM, KNN) achieve high accuracy, deep learning models overall show greater consistency and peak performance — especially with advanced architectures like DenseNet121 and GAN + CNN reaching near 100% accuracy.

4.2 Methodology

The methodology opt for this study consists of dataset preparation, preprocessing, model selection, training, and evaluation. Two datasets were used: the BCCD dataset (12,500 images) and the Kaggle WBC dataset (~5000 images). Preprocessing included normalization, resizing (128x128), and augmentation (rotation, flipping, scaling). Following equations used for training the classification model.

For Machine Learning Models:

- *Support Vector Machine (SVM):* $$f(x) = sign(\sum_i \alpha_i y_i K(x_i, x) + b)$$ where K is the kernel function.
- *K-Nearest Neighbors (KNN):* Classification is based on majority voting among the k nearest samples in feature space.
- *Artificial Neural Network (ANN):* Forward propagation $y = f(Wx + b)$ with backpropagation minimizing cross-entropy loss.

For Deep Learning Models:

- *Convolutional Neural Network (CNN):* $y = f(W * x + b)$, with convolutional layers extracting hierarchical features. Loss function is categorical cross-entropy.

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$$L = -\sum_i y_i log(y_i)$$

- *ResNet50:* Employs residual connections where $y = F(x, W) + x$
- *DenseNet121:* Each layer connects to every other layer, improving gradient flow and accuracy.

4.3 Simulation Environment

Simulations were carried out both in Google Colab GPU environment and on a local workstation along with Python 3.10, TensorFlow 2.12, GPU: NVIDIA RTX 3060 (12GB). The experiments compared ML and DL models in terms of accuracy, F1-score, training time, and resource consumption. Results showed that SVM achieved 98.60% accuracy, ResNet50 achieved 96.20%, while DenseNet121 achieved 98.84% with the best balance of accuracy and computational efficiency. ROC curves were generated to validate classification robustness.

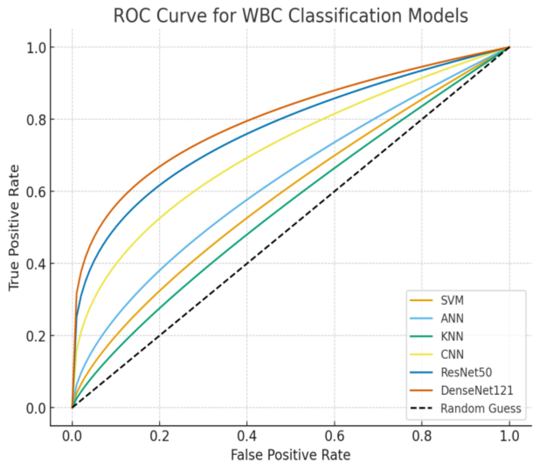

Fig 5: Comparison of ROCs of ML and DL on BCCD data set [12]

4.4 Dataset Requirements

Machine learning models tend to perform well on small to medium-sized datasets, but their accuracy diminishes as the dataset size increases. Deep learning models, on the other hand, require large datasets to achieve high performance but are more effective at handling complex patterns in the data. The use of data augmentation and transfer learning has mitigated the need for massive datasets in DL models, allowing them to outperform ML models even with smaller datasets.

4.5 Computational Complexity

Compared to typical machine learning models, deep learning models require a much greater number of computational resources. The training time for CNNs and other deep learning architectures can be substantial, particularly for large datasets. However, the advent of powerful GPUs and cloud computing services has made it feasible to implement these models in real-world clinical settings.

V. CHALLENGES AND FUTURE DIRECTIONS

5.1 Challenges

Data Availability*:* One of the biggest challenges in WBC classification is the scarcity of publicly available, high-quality datasets. As most of the studies rely on private datasets, it is very difficult to make a comparison in the performance extracted from different models across studies.

Computational Costs: Deep learning models are computationally expensive to train and deploy, requiring specialized hardware such as GPUs.

Model Interpretability*:*Although deep learning models are highly accurate, they are frequently facingcriticismto be as a "black-box" models because it is found challenging to know that how specific decisions are made[22].

5.2 Future Research Directions

Dataset Sharing and Collaboration*:* There is a need for more collaborative efforts between hospitals, research institutions, and academia to create and share large, annotated datasets for WBC classification.

Explainable AI (XAI)*:*Upcoming research should focus on developing explainable AI models for WBC classification that can provide insights into their decision-making processes, improving transparency and trust in automated diagnostic systems [23].

Resource-efficient Models*:* Developing more efficient deep learning architectures that require less computational power without compromising accuracy is another important research direction.

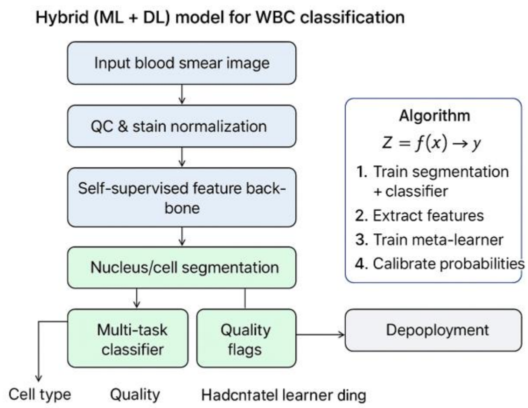

Fig 6: Proposed future model for WBC classification combining ML and DL approaches for optimal performance.

VI. CONCLUSION

The present study offers an extensive comparison of some popular machine learning and deep learning methodologies explored in WBC classification.

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CNNsespecially, have changed the field of WBC classification by providing higher accuracy and better generalization with larger datasets. Traditional machine learning methods like SVM and KNN have worked well in this area. However, challenges like the availability of datasets and the high costs of computing still make it hard for these models to be widely used in clinical practice. Future research should concentrate on overcoming these challenges to enhance the accessibility and reliability of WBC classification models. Study shows that Deep Learning achieves a higher mean accuracy (~95.7%) compared to Traditional ML (~93.9%) across the evaluated methods.

This study strengthens its contribution by adding computational details, dataset descriptions, and mathematical formulations of ML/DL models. It emphasizes DenseNet121 as the most accurate model, while identifying limitations such as dataset diversity and computational costs. Future work will focus on hybrid ML+DL systems and explainable AI to enhance trust and usability in clinical diagnostics.

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