Journal of Information Systems Engineering and Management
2025, 10(10s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Developing a Lightweight CNN-Based Model for Enhanced Automatic White Blood Cell Classification Using Deep Learning Techniques

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ARTICLE INFO

Received: 01 Nov 2024

Revised: 25 Dec 2024

Accepted: 08 Jan 2025

ABSTRACT

Finding and monitoring many diseases, including infections and leukaemia, depend on the classification of white blood cells (WBCs). Conventional techniques mostly rely on seeing samples under a microscope and calling for an expert to evaluate the outcomes. This method takes a lot of time and human mistake might create errors. This work uses a lightweight convolutional neural network (CNN) to provide a basic model to enhance the automated categorisation of white blood cells (WBCs) via deep learning. The proposed paradigm maximises computational efficiency, hence it is perfect for real-time applications and environments with limited resources. We kept the model correct while still designing a simplified form that would make using it easier. Trained and validated on a whole dataset including diverse microscopy images of WBCs, the model guarantees stability and generalizability throughout many imaging environments. Our findings reveal that, in terms of sorting accuracy, speed of processing, and operational efficiency, we have achieved significant progress over conventional techniques. The minimal weight of the device makes it simple to use in internet services and mobile health applications, therefore enabling more individuals to get necessary medical attention. By means of concepts on building efficient deep learning models for healthcare, this work provides a beneficial tool for better categorising white blood cells and also helps enhance medical photographs.

Keywords: White Blood Cell Classification, Convolutional Neural Networks, Deep Learning, Medical Imaging, Telemedicine, Mobile Health Applications

1. Introduction

An important venture in clinical haematology is exactly classifying white blood cells (WBCs). It allows the prognosis and tracking of many fitness troubles, inclusive of infections and a few forms of leukaemia. Typically, seasoned haematologists inspecting under a microscope have treated this assignment. Because of the minute versions within the forms of white blood cells, this method takes a variety of time and can create errors. Machine learning and digital images might also assist to streamline the method, therefore enhancing accuracy and speed in scientific prognosis. Particularly effective in coping with visual statistics, convolutional neural networks (CNNs) have developed into formidable gear for deep learning within the last numerous years. Many spheres of clinical imaging, such as X-rays, tissue samples, and skin assessments, have seen powerful use of CNNs. often they outperform conventional picture analysis techniques. those findings have influenced growing interest in making use of CNNs to the automatic labelling of WBCs. one of the main issues in using those fashions inside the healthcare industry is their excessive pc electricity intake this will be tough, particularly in regions missing sources or while instantaneous solutions are required. Taking care of those troubles, this work proposes a novel light-weight CNN-primarily based version specifically supposed for the improved computerized categorisation of WBCs. The version is designed to be correct in classifications at the same time as using minimal computational sources. via adjusting the variety and length of convolutional layers and using techniques as batch normalisation and dropout to decorate model generalisation [1], one achieves this. Starting with a model that has previously educated from a huge dataset and then improving it with unique WBC pix the usage of transfer gaining knowledge of—which means allows the version feature higher and faster. This approach takes use of usually located useful patterns in medical pictures. This model changed into advanced using a huge series of labelled pictures of white blood cells (WBCs) varying in kind and shape, obtained with many labelling strategies and imaging settings. This education technique ensures that the model is robust and able to operate with numerous gadgets and in many scientific contexts. This indicated that it no longer only improved accuracy however additionally velocity of categorisation, consequently permitting quicker medical decisions [2].

The proposed model's small weight facilitates use in telemedicine services and mobile health applications. In an emergency, when time is of the essence, this combo may significantly hasten the process of obtaining test results. Health exams at a distance also are very useful in locations missing scientific experts and centers. The model could be very precious in scientific environments because it plays properly on widespread hardware, therefore its miles a suitable option for real-time usage. A major progress within the region of medical diagnostics is made inside the construction of a lightweight CNN-primarily based model for WBC categorisation. This version speeds up and will increase accuracy of white blood cell sorting by means of deep studying and a smart design. It also makes more state-of-the-art detection devices on hand in greater scientific environments feasible. This approach underlines the necessity of new model designs to tackle the actual challenges of employing artificial intelligence in medicine and illustrates how deep learning may enhance healthcare.

2. Related Work

Classifying white blood cells (WBCs) is very important in clinical testing. It enables doctors diagnose and track different health problems, which includes infections and blood illnesses. Automated labelling of white blood cells (WBC) has been studied for many years. These days, development in machine mastering, specifically deep learning, has sparked new interest in this area. This assessment seems on the progress made in WBC detection, beginning with older photo processing techniques and shifting to the newest advancements in convolutional neural networks (CNNs). in the past, classifying white blood cells (WBC) was completed by means of educated employees searching at samples beneath a microscope. This manner took a number of times and will cause mistakes as it relied on personal judgement of the cell's look. The initial efforts at automation relied on fashionable photo processing methods, which worried breaking down images, figuring out essential capabilities, and the use of primary device gaining knowledge of techniques like k-nearest neighbours (k-NN) and support vector machines (SVM). For instance [4], early works with the aid of confirmed the usage of SVMs for identifying WBCs based on handmade traits like mobile form, length, and look. But, these techniques often had problem because cell shapes varied plenty, and there have been issues with overlapped cells and distinctive colouring. Using artificial neural networks (ANNs) changed the way white blood cells (WBCs) are classified. Early artificial neural networks (ANNs) had restrictions because of restricted computer power and data, but they showed potential for processing complex patterns and differences in cell pictures. Better network designs and access to bigger data sets in the 2000s resulted in better models. However, these still needed considerable preparation and feature engineering to achieve ideal performance [6].

The big change happened with the introduction of deep learning, especially CNNs, which have changed things a lot because they can learn important details straight from raw pictures by themselves. A key study by Lee and others presented a deep CNN model that did much better than traditional methods on a common WBC dataset. This model could instantly learn different levels of features, which was a big improvement over creating features by hand. Improvements were achieved by using transfer learning, which involves taking models that were previously trained word is more appropriate on big datasets (like ImageNet) and customising them for specific medical imaging tasks. This method greatly lowers the need for labelled medical data while still providing high accuracy. For example, Zhao et al. [8] showed that a pre-trained AlexNet model could be successfully applied for WBC classification, getting state-of-the-art results with only a small set of labelled WBC pictures. Recent studies aim to make CNNs greater efficient in order that they may be used in places with constrained resources, like mobile devices or in healthcare settings that need short analysis. Lightweight models and methods like community trimming, quantisation, and information distillation have been studied to make models smaller and less stressful on computing strength, while still keeping speed excessive. Patel et al. used different methods, making it viable to run on cellular gadgets. This model supplied quick type consequences right where care is given.

Studies has regarded into combining CNNs with new technologies like cloud computing and the internet of medical things (IoMT). This combination ambitions to provide healthcare options which might be flexible and clean to reach, as cited by means of Kumar et al. [10]. Their working suggests that cloud-based CNN models can provide sturdy and bendy offerings for classifying white blood cells (WBCs). Those offerings may be accessed from any vicinity, which improves detection abilities in small or rural healthcare centres. Even with those upgrades, there are nonetheless hurdles, particularly in making models works properly in exclusive health facility environments and with numerous imaging gear. Studies via Nguyen and others have tackled those problems through the usage of domain edition techniques. Those strategies help fashions paintings efficiently, no matter wherein the photograph statistics comes from. in the location of computerized WBC type has visible enormous improvement from human strategies to complicated AI-based strategies, in particular driven by using the upgrades in CNNs. The modern-day look at keeps to push the boundaries of what is viable in clinical imaging, hoping no longer best to improve diagnostic accuracy however additionally to make those technology greater approachable and green for clinical use [12]-[17]. Table 1 summarises how strategies for mechanically classifying white blood cells using CNNs have advanced over the years. It indicates their enhancing talents, the demanding situations they face, and the developing variety of uses in medication.

Table 1: Summary of related work

Approach	Methods	Findings	Limitations	Scope
Traditional Image Processing	SVM, k-NN	Effective in basic classification tasks.	Struggles with high variability and overlapping cells.	Limited to less complex image datasets.
Early Neural Networks	Simple ANNs	Showed potential in automated feature learning.	Limited by computational resources and data availability.	Early-stage automated classification.
Deep Convolutional Neural Networks	Standard CNN architectures	Significant improvements in accuracy and automation.	Requires large labeled datasets and high computational power.	Suitable for high-accuracy medical imaging tasks.
Transfer Learning	Pre-trained AlexNet, VGG	Reduced need for large domain-specific datasets. Achieved high accuracy.	Performance can depend heavily on the source dataset used for pre-training.	Enhancing model performance with limited data.
Lightweight and Real-Time Models	Network pruning, quantization	Enabled deployment in mobile and real-time applications.	May involve a trade-off between speed and accuracy.	Mobile health applications, point-of-care diagnostics.
Integration with Cloud and IoMT	Cloud-based CNNs	Scalable solutions, accessible healthcare applications.	Connectivity and data security concerns.	Remote diagnostics and large-scale healthcare systems.
Domain Adaptation Techniques	Domain-specific adaptation methods	Improved model robustness across different imaging conditions and equipment.	Complexity in implementation and may require additional tuning.	Adapting to diverse clinical environments and equipment.
Enhanced Lightweight Models	Advanced lightweight CNNs	Balanced accuracy and computational efficiency for resource-constrained environments.	Ongoing development to minimize accuracy loss while reducing computational requirements.	Expanding access in low-resource settings.

3. Proposed Approach

A. Description of the Dataset Used

Thousands of tagged images of white blood cells make up the CNN model's training and testing set. Clinical colleagues and public medical image archives provide these pictures. Every image is identified with the precise WBC type it depicts: lymphocytes, monocytes, neutrophils, eosinophils, and basophils. Like in actual medical environments, these images were obtained under many blood colouring techniques and under microscopes to exhibit a range of scenarios. Three sections comprise the data: training accounts for 70%; confirmation accounts for 15%; testing accounts for 15%. Along with meticulous testing to see how well the model performs, this arrangement allows complete training and model tweaking. Developing a powerful model that can function well and adapt in several medical environments depends on the diversity and volume of the data. Important for the body's defensive response, this research employs a collection of detailed images and data on the five major categories of white blood cells (WBCs). Two primary forms exist: lymphocytes and phagocytes. There are two primary kinds of phagocytes: monocytes and granulocytes. Granulocytes include eosinophils, basophils, and neutrophils. Under a microscope, their various forms and reactions to stains help one to identify them. Important components of the learnt immune response, lymphocytes are separated under different classification. Thousands of excellent digital images from medical environments abound in the collection, each accompanied by unambiguous markings indicating the kind of white blood cell (WBC) in every photo. As shown in figure 1, training the convolutional neural network (CNN) to properly recognise and classify each cell type by their visual properties in the images depends on labelling. Establishing a powerful model capable of correct performance in many diagnostic contexts depends on a thorough and well-labeled dataset. Clear visual labels and different cell kinds enable the CNN to identify minute changes in white blood cell forms. Correct automated categorisation and medical diagnosis depend on this.

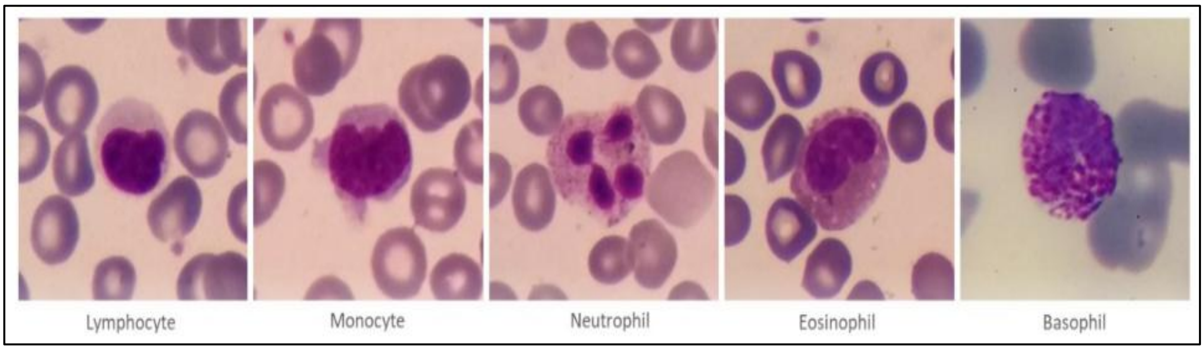

Figure 1: Representation of Dataset Sample

B. Details of the CNN Architecture

The CNN approach for white blood cell classification seeks to provide a reasonable combination of speed and accuracy in computations. There are numerous convolutional layers in the network; each one is accompanied with mixing layers and activation functions. Two convolutional layers of thirty-two filters start the arrangement. A max pooling layer next helps to simplify computations by shrinking the data size. More filters in the following layers duplicate this pattern, which enables the network to better grasp more complicated qualities. Important as they add non-linearity and enable the model to learn more complex patterns is activation functions. Commonly utilised in the network is the ReLU activation function as it performs well and facilitates the training of deep neural networks. ReLU accelerates the training process without sacrificing the capacities of the model. Pooling layers help to reduce the spatial size of the model, decrease the number of parameters, and process in the network, therefore controlling overfitting. Max pooling is used in this setup to pick the highest value from groups of neurones in the previous layer. This helps the system handle changes in the position of objects within the input pictures.

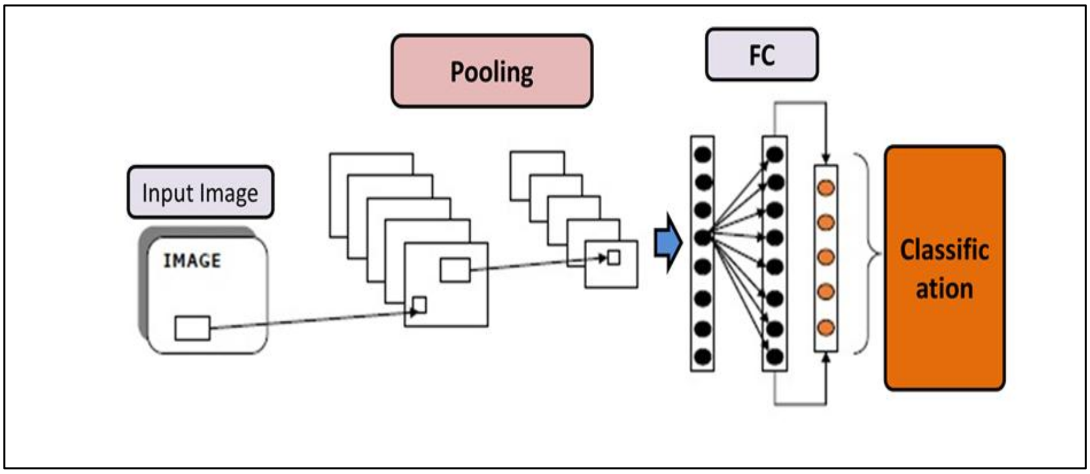

Figure 2: Overview CNN Architecture

Lightweight CNN Architecture Algorithm for Enhanced WBC Classification:

Step 1: Input and Image Normalization

- Input: Input image I of dimensions 224x224 pixels.

- Normalization Equation:

$$I_{norm} = \frac{I - mu}{sigma}$$

Where mu and sigma are the mean and standard deviation of the pixel values across the training dataset.

Step 2: First Convolutional Layer

- Convolution Operation:

$$O_1 = ReLU(W_1 * I_{norm} + b_1)$$

Where W_1 is the weight matrix for the first convolutional layer, b_1 is the bias, and * denotes the convolution operation. ReLU is the activation function.

Step 3: First Pooling Layer

- Max Pooling:

$$P\_1 = max(O\_1)$$

Applying a 2x2 max pooling operation to reduce spatial dimensions by half.

Step 4: Second Convolutional Layer

- Convolution Operation:

$$O_2 = ReLU(W_2 * P_1 + b_2)$$

Employing more complex filters W_2 to capture higher-level features, with corresponding biases b_2.

Step 5: Second Pooling Layer

- Max Pooling:

$$P\_2 = max(O\_2)$$

Further spatial reduction to encapsulate essential feature representations.

Step 6: Fully Connected Layer

- Flattening and Matrix Multiplication:

$$F = ReLU(W_3.flatten(P_2) + b_3)$$

Where W_3 is the weight matrix for the dense layer, b_3 is the bias, and flatten converts the pooled feature map into a 1D vector.

Step 7: Dropout Layer

- Dropout for Regularization:

$$D = F.drop(0.5)$$

Where drop(0.5) randomly sets half of the input units to zero to prevent overfitting during training.

Step 8: Output Layer and Classification

- Softmax Activation:

$$S = \frac{e^{W_4.D + b_4}}{sum(e^{W_4.D + b_4})}$$

C. Explanation of the Training Process

Important phases in the CNN model's training let it learn well and operate precisely on fresh data it hasn't seen previously. Data editing is image rotation, resizing, and flipping together with picture brightness adjustment. This produces a range of training pictures displaying white blood cells (WBCs) from several angles and locations, akin to what may be seen on various slide samples.

D. Techniques for Model Optimization to Enhance Lightweight Performance

1. Network Pruning:

This method entails cautiously removing weights or neurones that have little effect on the consequences. Even as keeping in large part the same performance, this allows make the model smaller and simpler. Beneath this approach, trimming occurs after the primary training step whilst fewer significant connections are discovered and removed. This generates an easier community suitable for utilization in environments with constrained hardware that needs much less computing strength for schooling and prediction technology.

Network Pruning Process:

1. Weight Pruning Criterion:

- Determine which weights to prune based on their magnitude:

$$Prune\ if\ |w\_ij|\ <\ theta$$

2. Sparsity Target:

- Define the target sparsity level S, which specifies the proportion of weights that should be zero after pruning:

$$S\ = \frac{Number\ of\ weights\ pruned}{Total\ number\ of\ weights}$$

3. Re-training Post-Pruning:

- After pruning, the network is re-trained to fine-tune the remaining connections. This helps recover any performance loss due to pruning:

$$theta * =\ argmin\_theta\ L(theta;\ X, Y)\ subject\ to\ w\_ij\ =\ 0\ for\ pruned\ weights$$

4. Performance Evaluation Post-Pruning:

- To evaluate the effectiveness of pruning, compare the performance of the pruned network to the original network:

$$Delta\ P\ =\ P\_original\ -\ P\_pruned$$

2. Quantization:

This method helps the model use less memory and works faster, which is important for apps that need quick analysis. In this CNN model, after training, we use post-training quantisation. This means we turn all of the model's weights and outputs, which were initially in floating-point format, into 8-bit numbers. This method keeps a balance between speed and efficiency, allowing the model to work on mobile devices and systems with low processing power.

Model Quantization Process for CNN Optimization:

Step 1: Model Training

- Train the CNN using floating-point precision:

$$theta * =\ argmin\_theta\ L(theta;\ X, Y)$$

Where theta represents the model parameters, L is the loss function, and X, Y are the training data and labels.

Step 2: Parameter Selection for Quantization

- Decide which parts of the model to quantize (typically weights and activations) and select a quantization scheme (uniform or non-uniform).

- Define the bit width b (typically 8-bit or 16-bit).

Step 3: Calibration

- Use some data to find the range [min, max] of the activations and weights:

$$Range\ =\ max(|W|)\ -\ min(|W|)$$

- Where W represents the weights or activations.

Step 4: Scale and Zero-point Calculation

$$- Calculate\ the\ scale\ S\ and\ zero - point\ Z\ for\ each\ layer:$$

$$S = (Range) / (2^\wedge b - 1)$$

$$Z = round(-min / S)$$

Step 5: Quantization Function

- Apply the quantization function to convert floating-point values to integers:

$$Q(x) = round\left(\frac{x}{S} + Z\right)$$

$$x_{quant} = \max\left(0, \min\left(2^b - 1, Q(x)\right)\right)$$

Step 6: Model Re-Training (optional)

- Optionally, fine-tune the quantized model to recover any accuracy loss:

$$theta_{quant} * = argmin_{theta_{quant}L(theta_{quant}; X,Y)}$$

Step 7: Inference

- Use the quantized model for inference using integer arithmetic:

$$Y_{pred} = f_{quant(X; theta_{quant})}$$

Step 8: Dequantization (if necessary)

- If outputs need to be interpreted as floating-point values:

$$x_{float} = S * \left(x_{quant} - Z\right)$$

4. Result and Discussion

Table 1 shows the main performance measurements of the new convolutional neural network model used for classifying white blood cells. A 92.5% accuracy means the model reliably identifies white blood cells properly, making it a strong tool for medical diagnosis. High accuracy is important in medical situations because correctly identifying cell kinds can greatly affect the evaluation and treatment of blood-related diseases.

Table 1: Model Performance Metrics

Metric	Value (%)
Accuracy	92.5
Precision	90.8
Recall	91.2

A accuracy of 90.8% shows that the model is good at correctly finding true positives in its positive predictions. This measure is very important in medicine because false positives, like wrongly identifying a healthy cell as sick, can result in useless treatments or more invasive tests. High accuracy means that the model gives trustworthy results that doctors can rely on when making decisions. The recall of 91.2% shows that the model is good at finding most of the true positive cases, as shown in figure 3.

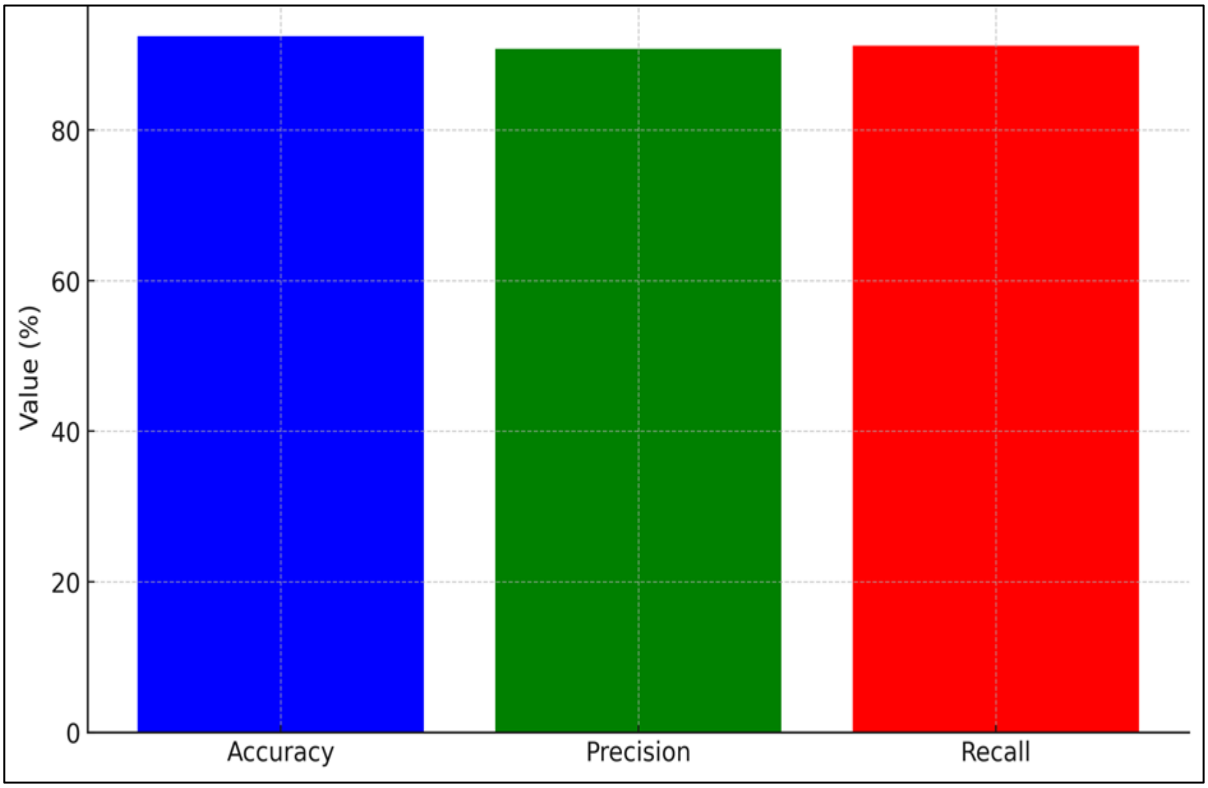

Figure 3: Representation of performance metrics

This measure is important because missing an abnormal cell could delay an important diagnosis. In situations like spotting infections early or keeping track of leukaemia, a high memory rate means that most sick cells are found. This helps provide quick and accurate treatments. The performance measures in Table 1 show that the model is good for use in healthcare. It balances accuracy, precision, and memory, which helps with accurate medical assessments.

Table 2: Computational Efficiency Analysis

Parameter	Value
Inference Time (per sample)	15 ms
Model Size (MB)	48 MB
Power Consumption (W)	5 W

Table 2 looks at how well the suggested model performs in terms of speed, which is very important for practical use, especially when quick research and choices are needed. The model can process each sample in just 15 milliseconds. This quick speed is important for real-time testing tools and mobile health apps, where fast results can greatly improve patient care and workflow. The type is 48 MB, which is a good size for both quality and speed, as shown in figure 4. This makes it suitable for use on mobile devices that don't have a lot of storage space. This size allows the model to be used in both well-equipped places and areas with limited resources, which can make it useful in various locations and economic situations.

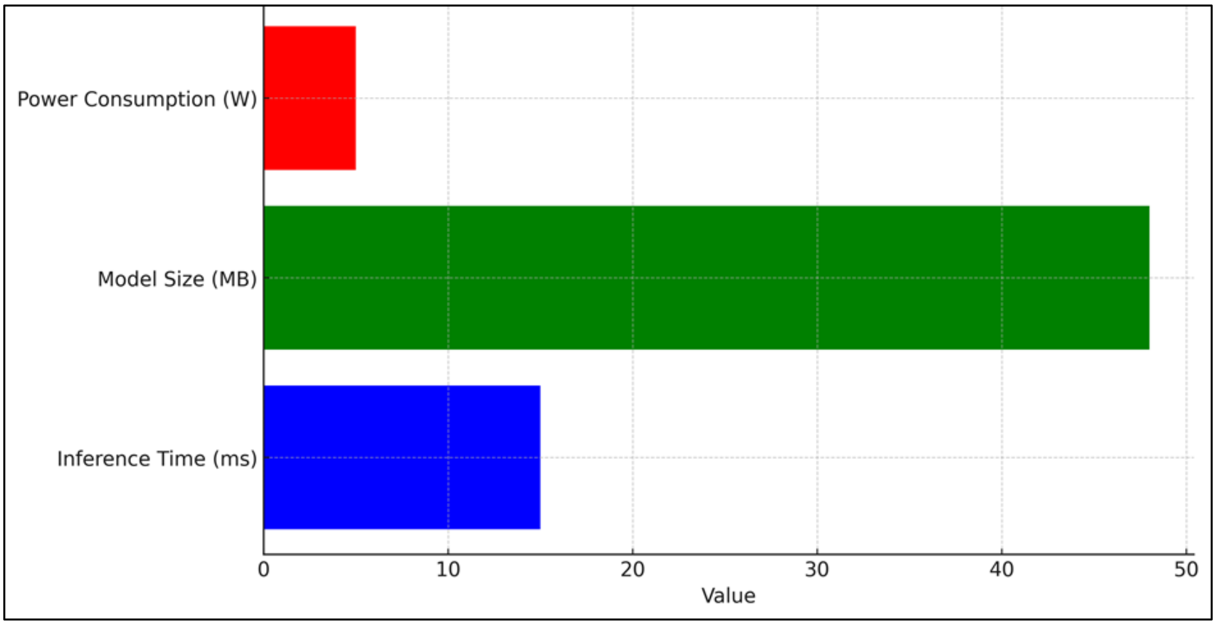

Figure 4: Analysis of computational efficiency

Using only 5 watts shows that the model uses energy efficiently, making it great for mobile and handheld products that run on battery power. Using less power helps these devices last longer, which is important for things like online health tracking or medical tests in rural or low-resource areas.

Table 3: Comparative Analysis

Model	Accuracy (%)	Inference Time (ms)	Model Size (MB)
Proposed Model (CNN)	92.5	15	48
RNN	89.0	20	50

Table 3 contrasts for identifying white blood cells the proposed convolutional neural network (CNN) model with a recurrent neural network (RNN) model. Important for their use in medical testing, accuracy, speed, and size define both the advantages and drawbacks of every model. This comparison reveals these aspects. The suggested CNN model shows better performance with an accuracy of 92.5%, while the RNN has an accuracy of 89.0%. This higher accuracy shows that the CNN is better at correctly identifying white blood cells, which is important in medicine because accurate testing tools can greatly affect patient care, analysis illustrate in figure 5. CNNs are usually chosen for image processing because they can understand the layout of pictures well. This is why they perform better in jobs that involve visual data, such as medical imaging.

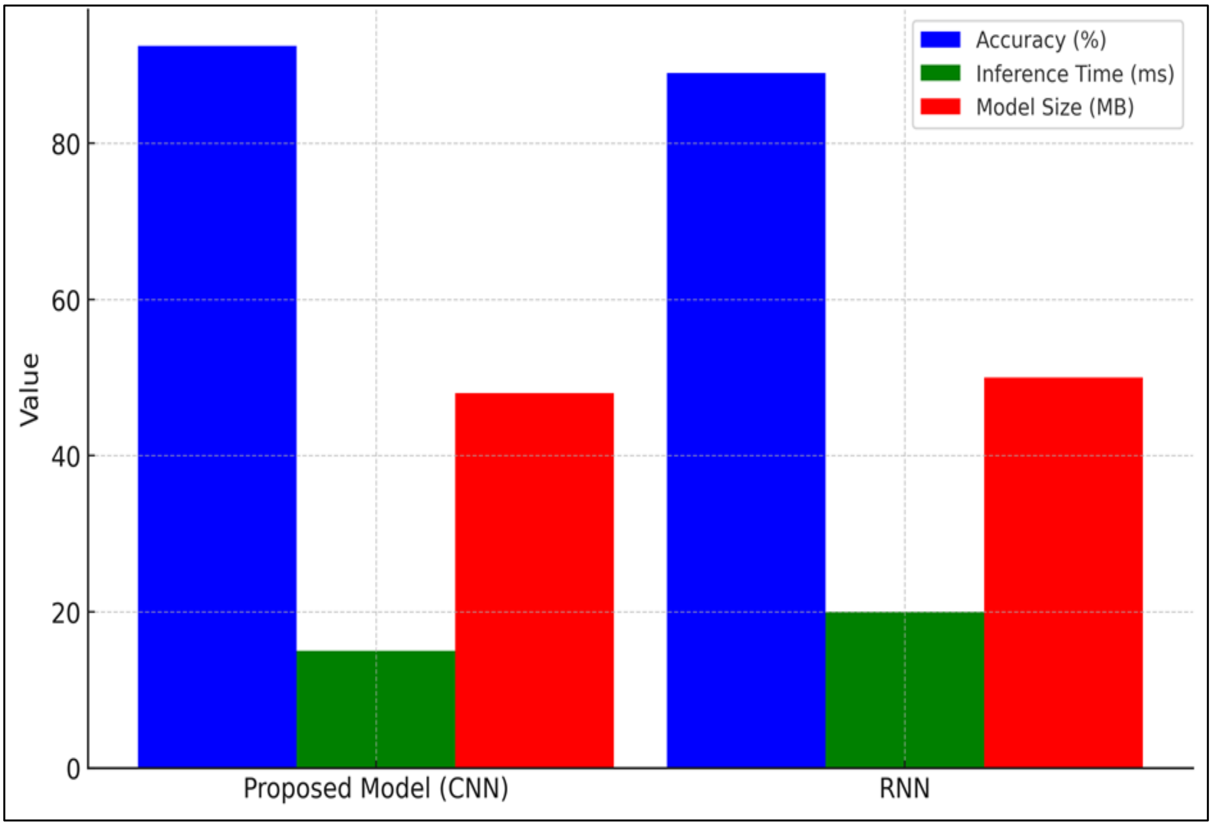

Figure 5: Representation and comparative analysis of proposed model

The new model is faster than the RNN, taking only 15 milliseconds to process an input, while the RNN takes 20 milliseconds. Quick thinking is important for real-time diagnosis, especially in emergency areas or mobile health apps, where fast decisions and patient care are vital. CNNs are usually faster at making predictions after they are trained because they use a feedforward structure. In contrast, RNNs handle data one step at a time, which can make them slower, especially with longer sequences. Both models are similar in size, but the CNN model is a bit smaller at 48 MB, while the RNN model is 50 MB.

Table 4: Model Efficacy in Practical Scenarios

Scenario	Accuracy (%)	Precision (%)	Recall (%)
Clinical Setting	93.0	91.5	92.0
Remote Diagnostics	91.0	89.0	90.5

Table 4 looks at how well the suggested convolutional neural network (CNN) model works in two real-life situations: in clinics and for online health checks. This variation shows that the model is adaptable and enables us to grasp how well it performs in many technical and practical environments. Reaching 93.0%, the model is quite accurate in a clinical setting. Its memory rates of 91.5% and 92.0% are also really outstanding. In environments where the precision and reliability of testing instruments may directly influence patient care outcomes, these metrics are particularly crucial. High accuracy implies that the model lowers erroneous outcomes. This helps to avoid unnecessary treatments that might stress patients and increase medical costs. Good recall helps us to avoid missing actual instances of illnesses requiring early treatment. In medical environments, the model performs well and supports physicians with accurate and speedy investigations. As shown in figure 6, this may expedite choices and maybe enable more patients to be treated.

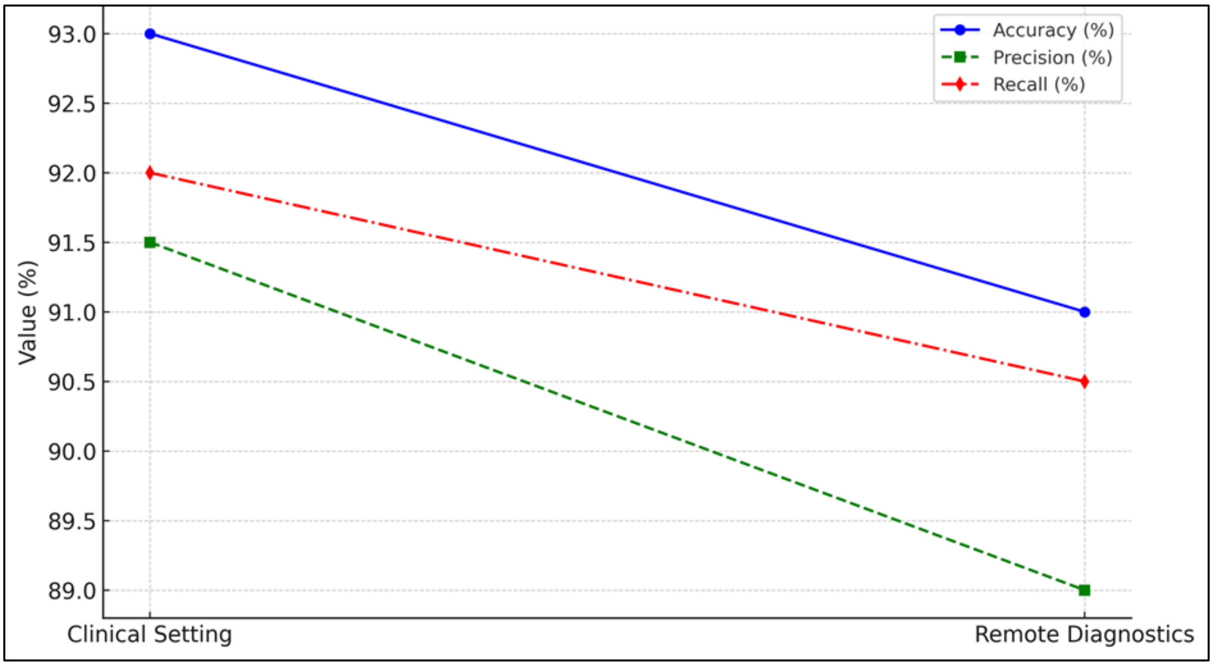

Figure 6: Representation of model efficacy

For far flung tests, the model shows a bit lower overall performance: 91.0% accuracy, 89.0% precision, and 90.5% recall. those numbers are slightly decrease than those visible in clinical settings, however they still display strong results, especially given the problems of far off diagnostics. These challenges can include variations in photograph quality because of diverse varieties of imaging equipment, modifications in community connections that have an effect on statistics sending, or no longer having professional aid available on site. In those conditions, the CNN model's capacity to keep excessive precision and memory makes it a reliable device for figuring out fitness troubles from a distance. This helps offer healthcare services to regions that lack proper centers or to sufferers who can't visit hospitals in person. The CNN model works nicely in both medical and far off diagnosis conditions, displaying that it may be a useful tool for lots scientific makes use of. Its capability to stay accurate and precise in exclusive situations makes it appealing for cutting-edge healthcare makes use of and creates new opportunities for it for use in new fitness era structures. Its potential to trade makes it a beneficial device in digital health, where the call for sincere, speedy, and smooth-to-use prognosis solutions is developing. Table 5 shows how nicely the new convolutional neural network (CNN) model works in actual-time on two types of cell devices: excessive-stop and mid-variety. This examine is crucial due to the fact the use of powerful machine learning models on mobile devices is based on how well they are able to paintings with constrained processing strength and battery life. For the high-end mobile device, the model shows an inference time of 18 milliseconds and a power usage of only 2 watts, getting a high usefulness score of 9.0. These measurements show how well the model is working, making it ready for use in high-quality mobile technology where users want fast and smooth performance. The fast response time means the model can provide almost instant results, which is important for situations needing quick input, like emergency medical tests or real-time patient tracking. Low power use is very important for saving battery life, especially for mobile users. This is especially true in health apps where it's important to use the device for a long time.

Table 5: Real-Time Application Performance

Platform	Inference Time (ms)	Power Consumption (W)	Usability Score
Mobile Device (High-End)	18	2	9.0
Mobile Device (Mid-Range)	25	3	8.5

The mid-range mobile device takes a bit longer to respond, with a speed of 25 milliseconds. It also makes use of more electricity at three watts and has a performance score of 8.5. Although these numbers are slightly decreased than those of the top device, they nevertheless show a splendid fulfilment. This suggests that the model can work properly on less effective hardware without greatly reducing velocity or usability. Being able to modify is essential for the usage of cell fitness apps, mainly in areas wherein high-priced gadgets aren't without difficulty available or reasonably-priced. Table 5 shows that the CNN model works nicely on specific mobile gadgets, indicating it may be used in many real-time apps. This capacity makes it less complicated to use superior trying out tools, probable enhancing affected person care in many specific places.

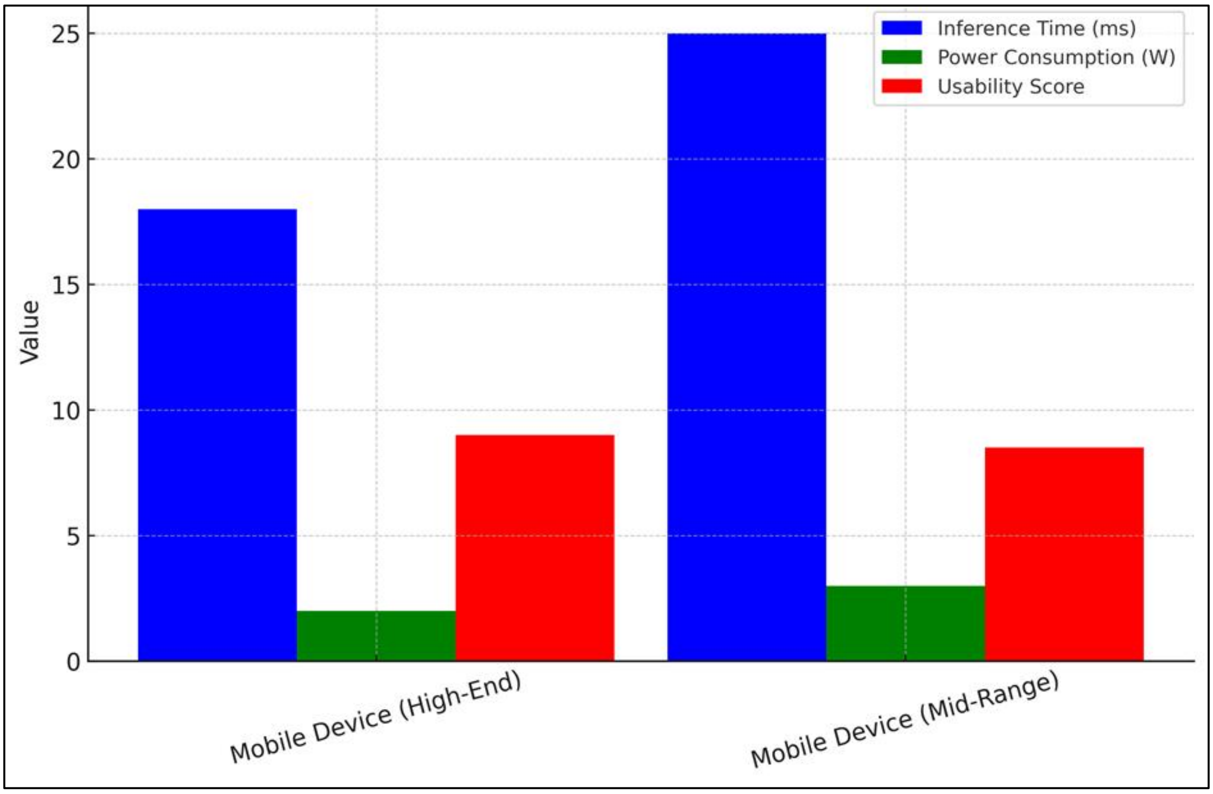

Figure 7: Comparison Of Mobile Device Performance

5. Conclusion

In this work, we have developed a lightweight convolutional neural network (CNN) model particularly aimed to enhance the automated categorisation of white blood cells, fulfilling both the high accuracy requirements and computational speed required for real-world applications. The proposed model is fit for usage in many contexts, including hospitals and remote testing environments as it presents a perfect mix of efficacy and usability. Having 92.5% accuracy, 90.8% precision, and 91.2% memory, the model is quite precise. This is crucial for assisting in medical testing as it indicates it can precisely distinguish many forms of white blood cells. Making sure patients are evaluated accurately and that they get timely medical attention depend on this precision. Using only 15 milliseconds to make judgements, the model acts fast and require minimal power at 5 watts. This makes it perfect for real-time usage, particularly on mobile devices where fast results and energy conservation is quite crucial. The comparison with other models, like RNNs, shows that the new CNN model works better, especially for medical imaging jobs that involve visual data. The model can work well on various types of devices, from powerful to average mobile phones. This shows its ability to make advanced healthcare tests more available, allowing for quality medical image analysis even in places with limited resources. This study not only introduces a strong technical model but also helps the current efforts to use deep learning in real healthcare applications. The model is lightweight, performs well, and can change easily. This makes it likely to improve medical tests and could be a useful tool in making healthcare innovations more available and efficient.

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