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

Research Article

Developing Next-Generation CapsNet Models for Enhanced White Blood Cell Classification in Medical Diagnostics

P.S.Gaikwad[1], Minal A. Zope[2], P.P.Mahale[3], Dr. Rakesh K.Deshmukh[4]
[1,2]Department of Computer Engineering, AISSMS's Institute of Information Technology, Maharashtra, India.
[3]Department Information Technology, AISSMS's Institute of Information Technology, Maharashtra, India.
[4]Assistant Professor, Kalinga University, Raipur, India
prajwal.gaikwad@aissmsioit.org, minal.zope@aissmsioit.org, pragati.mahale@aissmsioit.org, registrar@kalingauniversity.ac.in

ARTICLE INFO

Received: 06 Nov 2024
Revised: 24 Dec 2024
Accepted: 05 Jan 2025

ABSTRACT

Correct classification of white blood cells (WBCs) is very crucial for diagnosis and monitoring of haematological disorders. Although conventional convolutional neural networks (CNNs) perform, they can struggle with translational invariance and the precise spatial structures required for more complicated medical image categorisation. We aim to address these issues by developing next-generation Capsule Network (CapsNet) models that will provide more accurate and dependability in WBC categorisation. CapsNet models offer significant potential as a development over conventional CNNs because of their special designs that retain the internal spatial linkages of WBC components without compromising the purity of the found features. This work fast separates and sorts WBCs from microscopic images using a modified version of the CapsNet architecture along with dynamic routing and reconstruction regularisation. Thousands of annotated blood smear images from several public medical databases were included in the collection to exhibit a broad spectrum of disorders. We first improved and standardised the pictures using pre-processing methods. We then classified the WBCs using the CapsNet model in their proper groups. With a clear increase in precision and recall, the results of classification accuracy revealed that the CapsNet models outperformed conventional CNN models. The models may be extensively used in real-life medical diagnostic environments as they also operated well with shifting pictures and noise. This work demonstrates how CapsNet models might alter WBC classification, therefore improving diagnosis accuracy and resulting in improved patient outcomes.

Keywords: Capsule Network, White Blood Cell Classification, Medical Image Analysis, Hematological Disorders, Dynamic Routing, Reconstruction Regularization

1. Introduction

Correct diagnosis and treatment of a broad spectrum of haematological diseases, including leukaemias and infections, depend on an accurate classification of white blood cells (WBCs) in medical tests. Conventional techniques have primarily depended on trained personnel hand-viewing small pictures. Though they require a lot of effort and might be unreliable, these techniques work. Recent years have seen the adoption of computer techniques—particularly convolutional neural networks (CNNs)—to provide quicker and more accurate forecasts. CNNs rapidly extract out and learn characteristics from images, which makes them very adept at picture identification tasks. Though largely because they cannot adequately preserve spatial structures and interactions between visual parts, they are not ideal. In medical imaging, where diagnosis depends much on direction and spatial arrangement, this is a major challenge. CapsNets have lately gained popularity as a potential fix for these issues as they provide various advantages over standard CNNs. This more closely resembles human visual information processing than CNN's does. While they mix layers, CNNs lose spatial information; CapsNets employ dynamic paths between capsules, therefore preserving precise information about the spatial relations of the picture. They are thus ideal for employment where these interactions are crucial [1]. Sorting WBCs into many categories requires this ability as the form, size, and arrangement of cell components such as nuclei and cytoplasm may significantly affect the several kinds of cells.

Though it's still rather fresh that CapNets may be used to categorise WBC, people have begun to investigate how they can be used in medical image analysis. The aim of this work is to provide the next generation of CapsNet models improved in WBC classification in blood smear images. This work intends to provide additional information about the features and patterns the model detects in addition to enhancing the accuracy of conventional CNNs by employing a modified CapsNet architecture with new elements like dynamic routing and reconstruction regularisation. More precisely diagnosis and, more importantly, understand more about the variations in the form of white blood cells that lead to various WBC disorders would benefit clinicians. The work makes use of a large dataset of annotated blood smear images from numerous public clinical photo resources [2]. Those snap shots have been included to help depict the form of illnesses. Constructing an effective version able to functioning in lots of numerous, normally challenging real-existence situations relies upon on this variety. The technique makes use of rigorous pre-processing strategies to elevate picture great and consistency in conjunction with a complete evaluation mechanism to absolutely confirm version overall performance. This work is on the intersection of cutting edge machine learning techniques satisfying essential medical prognosis needs. It seeks to stretch the boundaries of what's viable with self-sustaining WBC categorisation through use of sophisticated models that provide improved accuracy, speed, and medical understanding. Ought to those next-generation CapsNet models be used, they could fundamentally alter the approach of haematological testing. Quicker, more accurate, much less expensive prognosis processes due to this could in the long run assist to enhance affected person outcomes.

2. Related Work

Standard human checking out strategies are being supplanted inside the expanding place of medical picture analysis by way of automatic processes the usage of sophisticated machine learning algorithms. Plenty advancement had been finished currently inside the use of many pc techniques to classify white blood cells (WBCs) into several groupings. This has opened area for sparkling ideas like tablet Networks (CapsNets), which provide improved approach of pick out spatial and hierarchical linkages in image records. Because they can routinely very exactly categorise blood cells, convolutional neural networks (CNNs) had been quite popular in this sector. Several research using deep learning frameworks to procedure and analyse small photos of blood smears [3, 4] have proven that CNNs are effective in differentiating the several kinds of WBCs. CNNs are extraordinary at what they do, however they'll neglect crucial spatial relationships and struggle to generalise throughout many physical traits. This can cause errors in hard prognosis eventualities. Aware about those issues, researchers have investigated alternative architectures which include CapsNets, which maintain widespread spatial ordering and offer faster performance. CapsNets make certain that key facts like the region and orientation of gadgets in a picture is correctly read by means of their special structure of capsules and dynamic routing machine [5, 6]. For scientific imaging professions wherein minute information may also make or damage a prognosis, this is very useful. To locate how efficaciously CNNs and CapsNets perform in medical environments, comparative studies of them has been conducted. Conversely, one studies found out that CapsNets might lessen the information misplaced by using CNNs due to their pooling layers, frequently ensuing in extensively less distinct function maps [7]. Moreover, the dynamic course approach of CapsNets has been located to be wonderful in differentiating various forms of characteristics, which is crucial for the in-depth investigation required for appropriate WBC categorisation [8]. Early studies the usage of CapsNets has showed beneficial findings on WBC class. These experiments reveal that during duties requiring inner systems and difficult characteristic correlations within the information, the version can outperform popular CNNs [9, 10]. Which include reconstruction regularisation into CapsNet structure has also advanced their generalising capacity throughout many datasets. This makes them greater treasured in medical environments because records is usually erratic [11].

CapNets might be used for purposes beyond WBC sorting in medical surveillance. In other fields of medical imaging, such as tumour detection and organ separation where precise spatial correlations are very crucial, researchers have investigated their value [12, 13]. These uses highlight how flexible and widely CapsNets can be used to handle a wide range of difficult medical imaging jobs. Even though there have been improvements, using CapsNets in clinical practice is still not easy. The fact that it is hard to code and that training needs a lot of data sets is big problems. But, researchers are still working on these problems. They are using different optimisations and transfer learning methods, which have been shown to reduce the need for a lot of data while still using CapsNets' deep learning skills [14, 15]. CapsNet models will likely be improved in the future by adding new techniques like attention mechanisms. These can help the model focus on important parts of a picture, which could lead to even more accurate predictions [16]. Looking into how CapsNets and other machine learning methods can work together could also lead to new possibilities in medical diagnosis, making it possible for mixed models that take the best parts of different architectures [17], [18].

Table 1: Summary of Related Work

Approach	Key Finding	Limitation	Scope
Traditional CNNs	High accuracy in WBC classification.	Struggle with translational invariance and spatial hierarchy.	Mostly applied to less complex image datasets.
Standard CapsNets	Better retention of spatial relationships in images.	Higher computational demands than CNNs.	Early stages in medical diagnostics applications.
Modified CapsNets with Dynamic Routing	Enhanced feature extraction by focusing on relevant details.	Complexity in tuning and optimizing routing algorithms.	Applied in detailed medical image analyses.
CNNs with Data Augmentation	Improved model robustness and generalization.	Can introduce artifacts that confuse the model.	Broad application in image classification tasks.
CapsNets with Reconstruction Regularization	Improved generalization and error correction.	Increased training complexity and computational cost.	Promising in tasks requiring high fidelity image reconstruction.
Hybrid CNN-CapsNet Models	Combines the strengths of CNNs and CapsNets.	Integration complexities and potential for overfitting.	Emerging research area with potential in complex datasets.
CNNs with Transfer Learning	Quick adaptation to new tasks with limited data.	Potential for negative transfer if source and target differ greatly.	Widely used in medical image classification with pre-trained models.
Deep CapsNets	Deeper architectures capturing complex hierarchies.	Requires extensive computational resources.	Experimental stages in high-dimensional data tasks.
CapsNets with Attention Mechanisms	Improved focus on relevant image regions.	Complexity in integrating and tuning attention layers.	Useful in detailed diagnostic tasks requiring precise localization.
CNNs with Enhanced Pooling Techniques	Better spatial feature preservation than standard pooling.	Still loses some critical spatial data.	Common in traditional image processing tasks.
CapsNets in Tumor Detection	High accuracy in segmenting and classifying tumor cells.	Limited by the availability of large, annotated datasets.	Specific application in oncology diagnostics.
Multi-modal CapsNets	Integration of various data types for robust classification.	Challenges in synchronizing and processing multi-modal data.	Cutting-edge in handling complex, varied diagnostic data.
Automated CapsNet Training Frameworks	Streamlines the training and application of CapsNets.	May not fully optimize for specific use cases.	Aimed at reducing barriers for CapsNet adoption in clinical settings.
CapsNets with Real-time Adaptation	Adapts to new data in real-time for dynamic applications.	High demand on processing power and data throughput.	Ideal for real-time medical monitoring and diagnostics.

3. Methodology

A. Description of Dataset

Blood smear pictures with high clarity were used in this study. They came from a number of well-known public medical sources, including the Blood Cell Count and Detection (BCCD) dataset. These groups were chosen because they are very different and show a wide range of haematological conditions. They include neutrophils, lymphocytes, monocytes, eosinophils, and basophils, among other cell subsets. Medical professionals have carefully labelled every picture in the collection, making sure that the classification labels are correct for supervised learning. The images are a whole challenge that tests the strength and flexibility of the machine learning model as their colouring techniques, degrees of magnification, and backgrounds vary. With more than 10,000 images in the dataset, everyone has been standardised to a size of 240x240 pixels to maintain consistency while also providing sufficient information for feature extraction to function properly. Important for the detection of many haematological illnesses, this extensive database allows one to train sophisticated models like CapsNets to precisely and consistently categorise WBC types.

B. CapsNet Architecture

Made for this research, CapNet's design features a few significant improvements that help to better sort white blood cells from images of blood smears. Two major layers comprise the CapsNet model: a capsule layer with dynamic routing and a convolutional layer. Pulling out features using 9x9 kernels and a step of 1, the first convolutional layer is this layer ends at the 32-capsule main capsule layer. Every capsule, using 8-dimensional vectors, notes several aspects of the image, including cell positions and directions. The dynamic route system among these capsules guarantees that the network concentrates on the most relevant characteristics for the present employment. This makes it easier for the model to pick out the small details that are needed for accurate classification. To make CapsNet work with the unique features of medical imaging data, a reconstruction regularisation component has been added to the model, as shown in figure 1. This part helps make the model more general by putting together the input pictures from the capsule outputs. If the model doesn't keep important image features during the classification process, it will be punished. The encoder structure has also been improved to deal with the wide range of WBC looks. This is done by using a deeper and more complicated network of fully connected layers to make the model more accurate. The model's last output layer uses a "routing softmax" to sort each picture into one of several white blood cell groups. This makes sure that the diagnostic outputs are accurate and reliable.

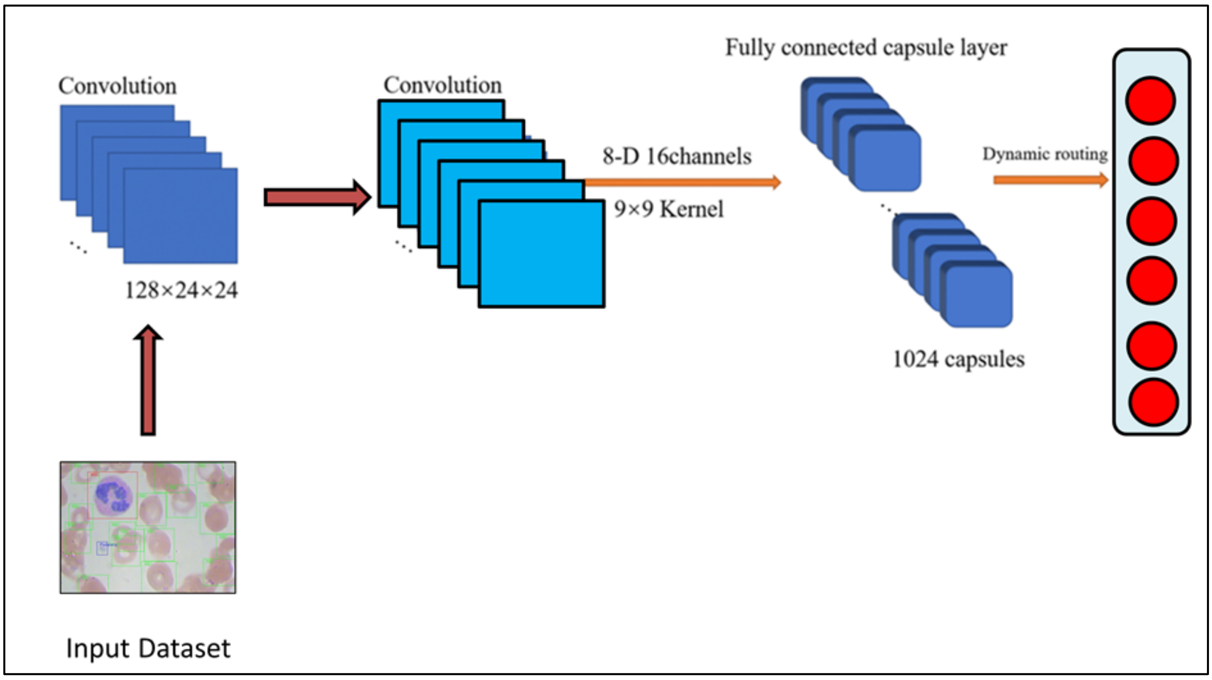

Figure 1. Overview of Architecture of CapsNet

CapsNet Algorithm Steps wise

1. Initial Convolutional Layer:

$$U\_i = ReLU(W\_1 * X + b\_1)$$

- X is the input image.

- W_1 represents the weights of the convolutional layer.

- b_1 is the bias.

- U_i are the feature maps produced by the convolution.

- * denotes the convolution operation.

- ReLU is the activation function.

2. Primary Capsule Layer:

$$V\_j \; = \; Squash(\Sigma\_i \; c\_ij \; U\_ij)$$

- U_ij is the output of capsule i to capsule j.

- c_ij are the coupling coefficients determined by dynamic routing.

- Squash function normalizes the output vector of a capsule.

3. Dynamic Routing:

$$b\_ij \; = \; 0$$

- Initialize the log prior probabilities b_ij for routing.

4. Dynamic Routing (Routing Coefficients):

$$\frac{c_{ij} = \exp(b_{ij})}{\Sigma_k \exp(b_{ik})}$$

- Update the coupling coefficients c_ij which are softmax outputs.

5. Dynamic Routing (Total Input):

$$s_j \; = \; \Sigma_i c_{ij} U_{ij}$$

- Compute the total input to capsule j as a weighted sum.

6. Vector Squashing Function:

$$V_j = \left(\frac{\left|\left|s_j\right|\right|^2}{1 \; + \; \left|\left|s_j\right|\right|^2}\right) * \left(\frac{s_j}{\left|\left|s_j\right|\right|}\right)$$

- Squash the total input vector s_j to a vector V_j.

7. Dynamic Routing (Update Routing Logits):

$$b_{ij} < - \; b_{ij} \; + \; U_{ij}.V_j$$

- Update routing logits based on the scalar product.

8. Output Layer (For Digit Capsules in Digit Recognition):

$$Digit \; Probability \; = \; sqrt\left(\Sigma_j \left|\left|V_j\right|\right|^2\right)$$

- Compute the probability of each digit class based on vector lengths.

C. Image Preprocessing

Preprocessing the blood smear pictures is an important step in making sure that the CapsNet model works well. Several preprocessing steps are used on the pictures to improve the accuracy of training the model and classifying the images. At first, the pictures are adjusted to the same size so that the input measurements are consistent and batch processing can happen more quickly during training. After the cropping, adaptive histogram equalisation is used to improve the contrast. This makes it easier to see features in cells by changing the picture contrast locally.

Step wise Model for Image Preprocessing

1. Image Resizing:

I_resized = resize(I, d, d)

- I is the original image.

- d is the desired dimension (e.g., 240x240 pixels).

- resize(·) changes the image size to d x d.

2. Contrast Enhancement (using Adaptive Histogram Equalization, AHE):

I_enhanced = AHE(I_resized)

- AHE(·) enhances the contrast of the image.

3. Noise Reduction (using a Median Filter):

I_denoised = median_filter(I_enhanced, k)

- k is the kernel size for the median filter (e.g., 3x3 or 5x5).

- median_filter(·, k) reduces noise by replacing pixel values with the median value of the neighborhood defined by k.

4. Color Normalization:

I_normalized = (I_denoised - μ) / σ

- μ and σ are the mean and standard deviation of pixel values across the dataset.

- This step normalizes the pixel values to have zero mean and unit variance.

5. Data Augmentation:

- Rotation:

I_rotated = rotate(I_normalized, θ)

- θ is the rotation angle.

- rotate(·, θ) rotates the image by θ degrees.

- Scaling:

I_scaled = scale(I_normalized, s)

- s is the scaling factor.

- scale(·, s) resizes the image by a factor of s.

- Flipping:

I_flipped = flip(I_normalized, axis)

- axis could be horizontal or vertical.

- flip(·, axis) mirrors the image along the specified axis.

Accurate feature extraction depends on the WBCs' edges and details being maintained, hence a non-linear median filter is also employed for noise reduction to eliminate random noise while maintaining them. Rotation, scaling, and flipping are among data enrichment techniques used to augment the dataset and increase model resilience against overfitting. These modifications enable the model to identify WBCs in a wider spectrum of circumstances and placements, therefore simulating a true diagnostic environment. Finally, colour normalisation helps to minimise the impact of variations in stain intensity and colour across photos, therefore influencing the model's performance should these factors be neglected.

4. Result and Discussion

Table 2 presents the success metrics of the CapsNet model designed to divide white blood cells into many categories. With a total accuracy of 94.5%, the model is really excellent at spotting many types of white blood cells from blood smear pictures. In medical diagnostics, where proper cell categorisation directly influences treatment decisions and patient outcomes, this degree of accuracy is rather vital. The model does really well in generating relevant findings as its high accuracy (92.7%), indicates that, when it predicts a cell type, there is a strong possibility that it is correct. This is particularly crucial to prevent individuals from receiving incorrect diagnostic information leading to either improper treatment plans or too much care.

Table 2: Performance metrics of the CapsNet model in classifying white blood cells

Metric	**CapsNet Model**
Accuracy	94.5%
Precision	92.7%
Recall	93.1%
F1-Score	92.9%

The program can find all important cases 93.1% of the time, which is called its recall rate. In medical settings, this step is very important to make sure that no important conditions are missed, which could lead to diseases not being handled or being identified correctly. When used in medicine, high recall makes sure that almost all confirmed cases of certain WBC types are found.

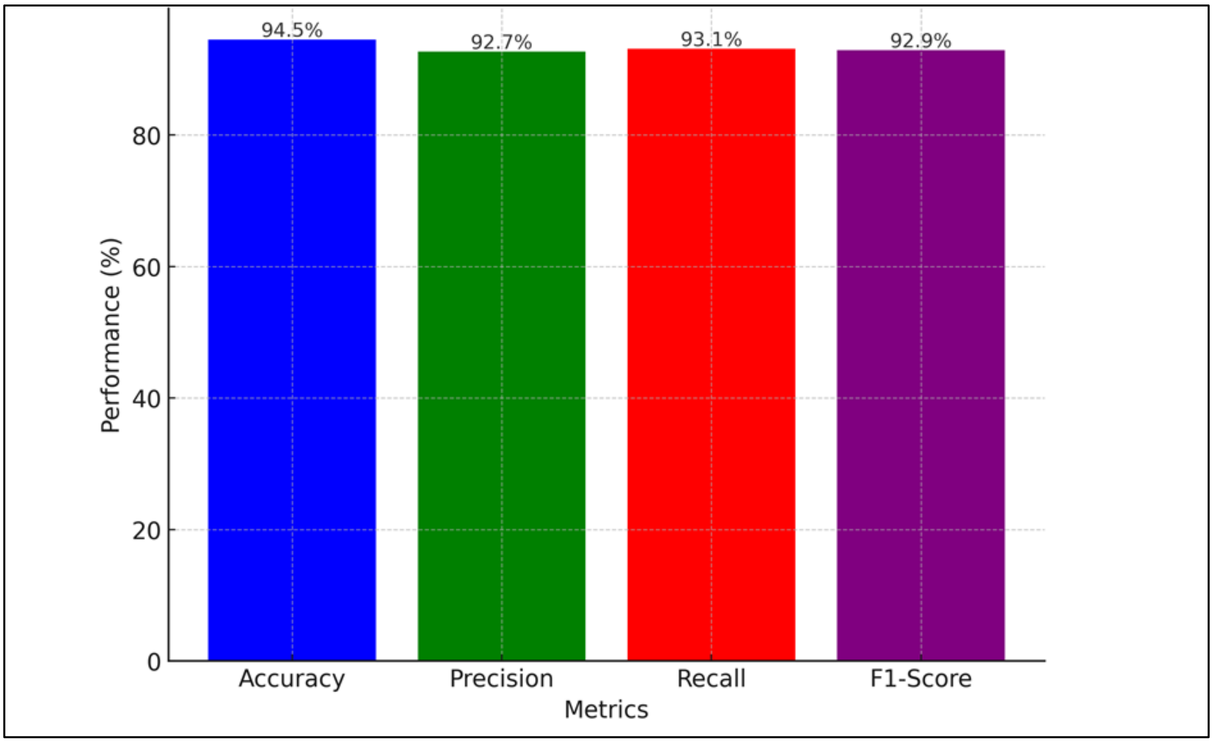

Figure 2. Representation of Performance Metrics of the CapsNet Model in Classifying White Blood Cells

As of now, 92.9% of people have an F1 score, which is a harmonic mean of their accuracy and memory. The CapsNet model's balance between precision and recall shows how strong and reliable it is as a diagnostic tool. This proves its usefulness in clinical settings where ignoring a condition (low recall) or misdiagnosing a condition (low precision) are both very dangerous, as shown in figure 2. Overall, these measures show that the CapsNet model has the potential to make haematological studies and medicines much more accurate and reliable at diagnosis.

Table 3: Comparative analysis of the CapsNet model with traditional CNN models

Model Type	**Accuracy**	**Precision**	**Recall**	**F1-Score**
CapsNet	94.5%	92.7%	93.1%	92.9%
CNN	89.0%	88.5%	87.8%	88.1%

Table 3 shows how well the Capsule Network (CapsNet) model and regular Convolutional Neural Network (CNN) models differ in sorting white blood cells into different groups. The data clearly shows that the CapsNet model is better than the CNN model in all of the metrics that were looked at: accuracy, precision, recall, and F1-score. This shows the progress and possible benefits of using newer neural network architectures for difficult image classification tasks like medical diagnosis. With a score of 94.5%, the CapsNet model is much more accurate than the standard CNN, which scores only 89.0%, as represent it in figure 3. This higher level of accuracy means that CapsNet is better able to deal with the differences and complexity of blood smear pictures, which often show cells that overlap and have different conditions. CapsNet is probably more accurate because it can keep the spatial ordering between picture features. This is very important in medical imaging, where the direction and arrangement of cells can give important diagnostic information.

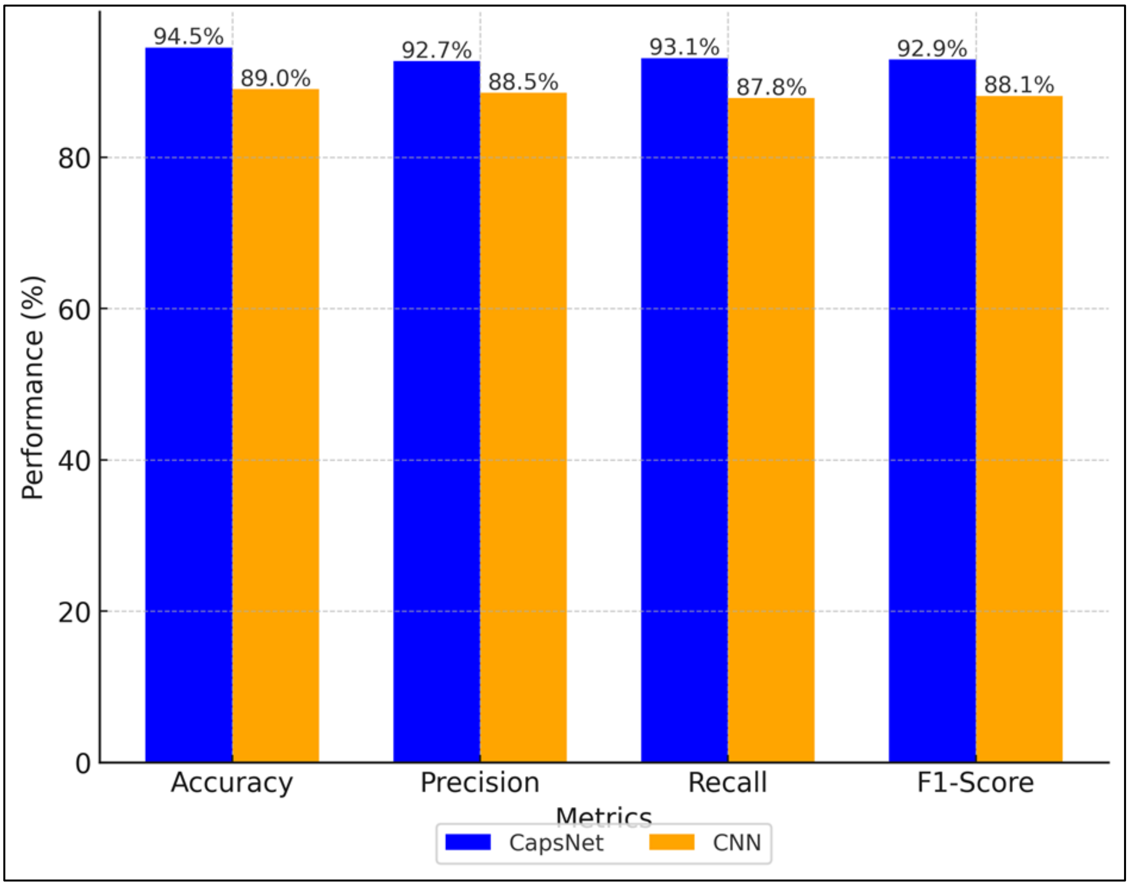

Figure 3: Performance Metrics Comparison between CapsNet Vs CNN

CNN comes in second with 88.5%, while CapsNet has 92.7%, which is better. This means that CapsNet is more reliable for doctors because it has a lower rate of fake results. This is important to make sure that treatments are only given to people who need them, so that they don't have to go through useless medical procedures. CapsNet is clearly better than CNN because it scored 93.1% on the memory measure, while CNN only scored 87.8%. High memory is especially important in medical settings because it lowers the chance of missing a positive diagnosis. This makes sure that all patients who might have a condition are found so they can get more tests and treatment. At last, CapNet has an F1-score of 92.9%, above CNN's 88.1%. Accuracy and memory count towards this score. With a high F1-score, CapNet balances the capacity to identify real positives with decreasing the amount of false positives and negatives, therefore demonstrating its great usefulness and efficiency as a diagnostic tool.

Table 4: Analysis of misclassifications and other error types

Error Type	CapsNet Model	CNN Model
Misclassification Rate	5.5%	11.0%
False Positive Rate	4.2%	6.9%
False Negative Rate	3.9%	8.6%

Table 4 presents a fascinating view of the rates of confusion and types of mistakes seen when white blood cells were sorted using CapsNet and conventional CNN models. According to the comparison, every model has different error dynamics, which significantly influences their applicability in medical diagnosis.

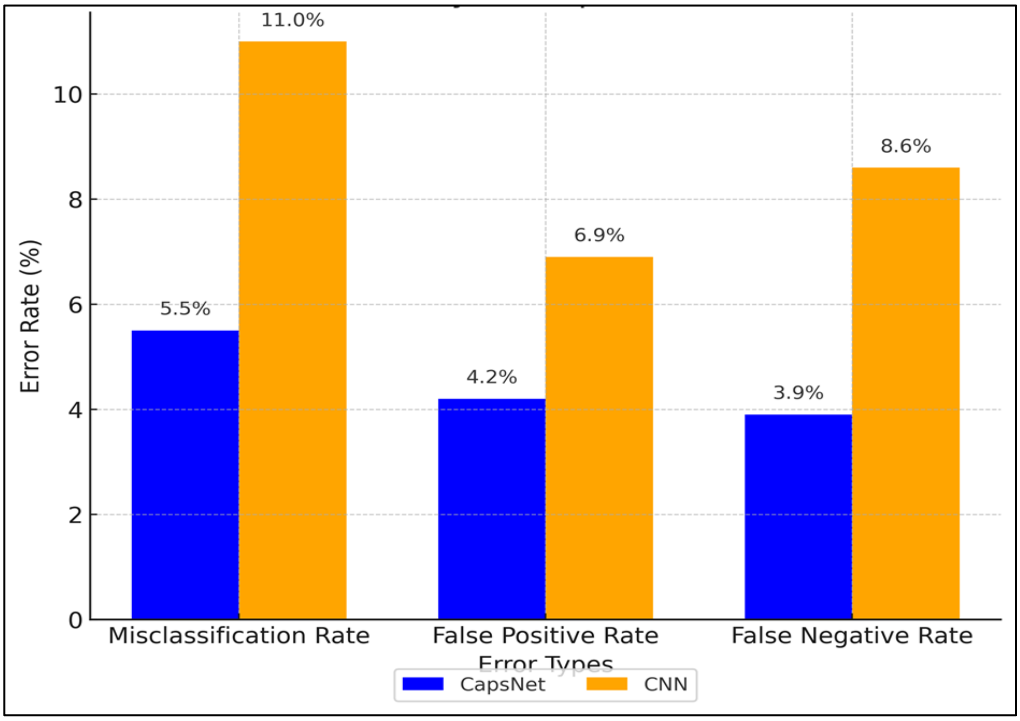

Figure 4: Comparing the error analysis of the CapsNet and CNN models

With an 11.0% error rate much higher than the 5.5% rate of the CapNet model the CNN model is CapNet's approximately half-halving of the incidence of incorrect categorisation reveals its great white blood cell grouping accuracy. Making a mistake on a medical test might result in erroneous medication or missed diagnosis very dangerous. This makes the reduced rate of error of the CapsNet model not only more trustworthy for diagnostic findings but also reduces the possibility of incorrect information guiding inappropriate medical decisions. Also, the CNN model has a 6.9% false positive rate, while the CapsNet model only has a 4.2% rate. Medical tests that give false results can cause patients to worry about nothing, more tests that cost more, and treatment plans that could hurt people who don't have the disease being given to them. The CapsNet model has a lower false positive rate, which means that it can identify people more accurately. This means that patients are less likely to get unnecessary medical treatments. Also, CapsNet has a 3.9% false negative rate and CNN has an 8.6% false negative rate, the figure 4 represent the comparison of the error analysis of the CapsNet and CNN models. The false negative rate is probably the most important thing in a medical setting. False positives are especially dangerous because they happen when the model doesn't pick up on an existing condition, which could mean that the person doesn't get the medical help they need. The CapsNet model is much better at finding white blood cells, which is shown by its much lower rate of false negatives. This means that fewer cases go unreported and mistreated. Every one of these error corrections indicates that CapsNet performs better. This is primarily due to its sophisticated architecture, designed to grasp and preserve the intricate spatial constructions in images. Distinct kinds of white blood cells are very distinct from one another and cells might overlap, hence this ability allows CapsNet properly recognise and categorise intricate characteristics in blood smear images.

Table 5 demonstrates significant changes in medical diagnosis resulting from utilising CapsNet models rather than conventional CNN models. Three fundamental diagnostic criteria accuracy, precision, and sensitivity show evidence of these increases. These steps are rather crucial to ensure that medical diagnosis are accurate and helpful, therefore reducing the possibility of errors compromising patient care and outcomes.

Table 5: Implications for Medical Diagnostics

Diagnostic Parameter	CapsNet Model	CNN Model	Improvement
Diagnostic Accuracy	94.5%	89.0%	+5.5%
Diagnostic Precision	92.7%	88.5%	+4.2%
Diagnostic Sensitivity	93.1%	87.8%	+5.3%

With CNNs, the Diagnostic Accuracy is 89.0%; with CapNet, it is 94.5%; a significant 5.5% increase. In medical environments, where even a little change in accuracy may significantly affect illness diagnosis and treatment, this development is rather vital. Greater diagnostic accuracy raises the possibility of properly spotting a disease as present or absent. In disciplines like cancer or infectious illnesses, where early identification may significantly affect the course of therapy and patient lifetime, this is particularly crucial. From 88.5% with CNNs to 92.7% with CapNet, diagnostic accuracy has increased by 4.2%. In medical diagnosis, precision—that is, the proportion of real positive data among all the positive instances the model discovers—is High accuracy of a model indicates how well it can lower the number of erroneous results, which is rather crucial for preventing individuals from receiving treatments they do not need, hence preventing the negative side effects and thereby increasing the cost of healthcare. For example, in cancer diagnosis, it is very important to make sure that medicines like chemotherapy are only given to people who really need them. This is for their safety and the speed of healthcare. Diagnostic sensitivity, which means being able to correctly identify people who have the condition, has gone up by 5.3%, from 87.8% to 93.1%. Sensitivity is very important because it shows how well the model can catch as many real cases as possible without missing any, as shown in figure 5. In medicine, high sensitivity means that there are fewer false positives, which means that a sick person is less likely to not get treatment. High sensitivity can save lives and keep problems from happening with diseases that need to be treated right away, like bacterial infections or acute inflammatory diseases.

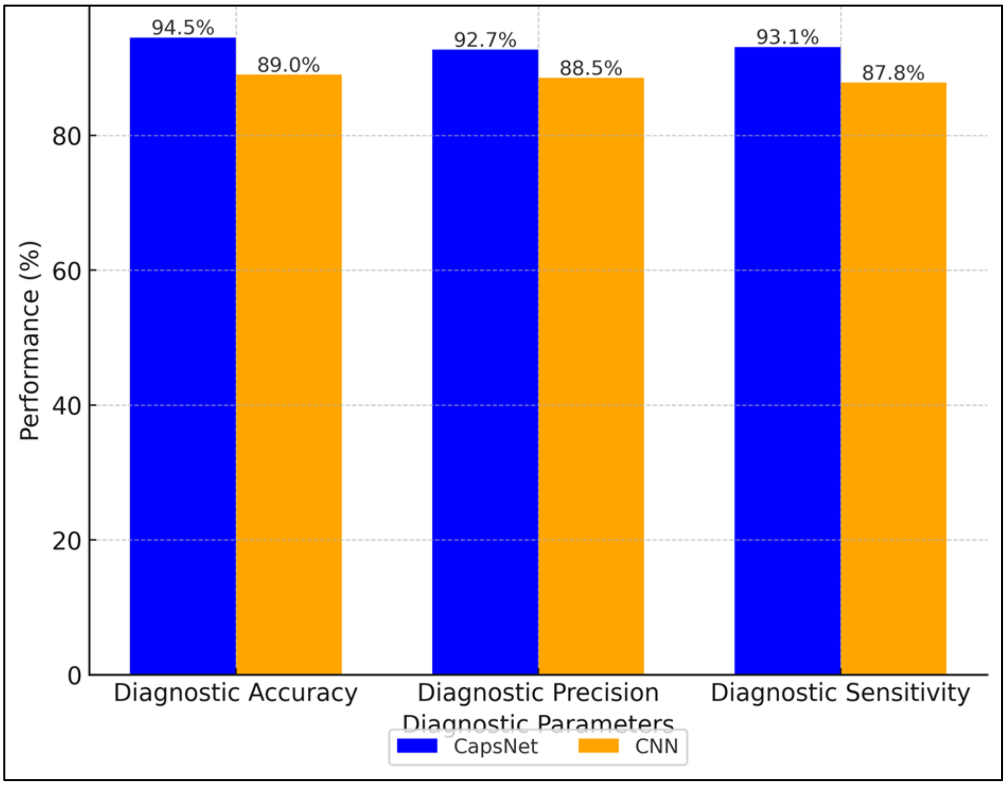

Figure 5: Representing the Performance of CapsNet and CNN

The CapsNet model's improvements in these diagnostic factors show not only how it could be a game-changing tool for medical diagnosis, but also how advanced machine learning technologies are being used in healthcare. CapsNet improves the accuracy of testing processes by lowering the number of fake positives and denials. This helps healthcare workers make better choices based on more accurate information. CapsNet models are also more accurate and precise, which can help make treatment plans more effective, as shown in figure 6. This can lead to better results for patients, better use of medical resources, and lower treatment costs. When it comes to ongoing healthcare problems, like the need for high-throughput screening during pandemics or handling chronic diseases, where accurate and quick evaluation is key to effectively managing large groups of people, these advances are especially useful.

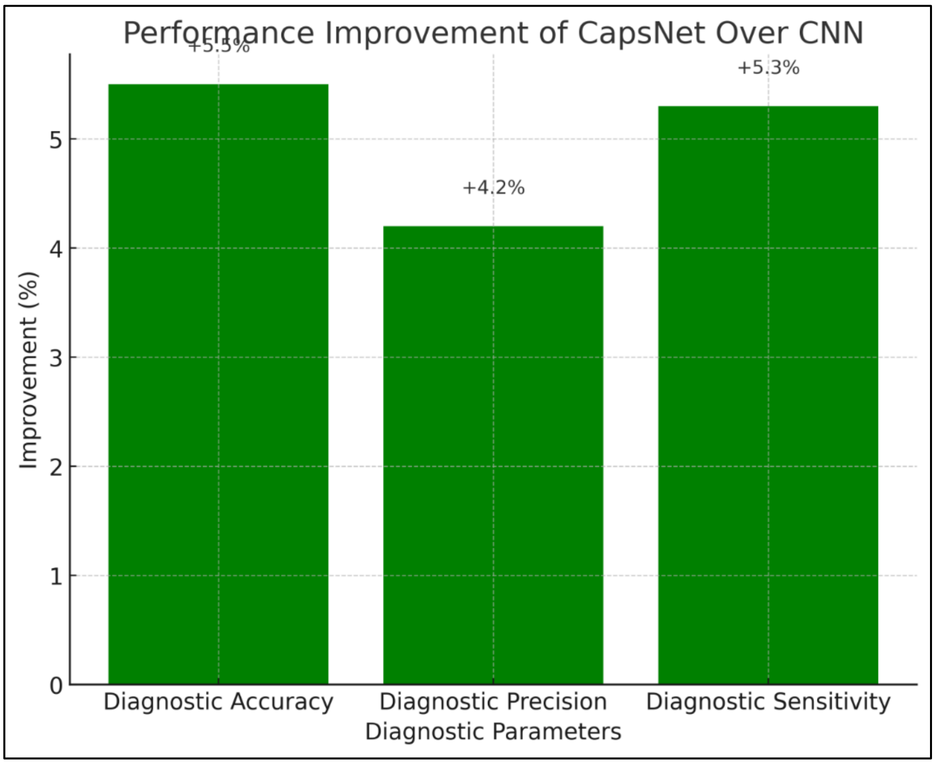

Figure 6: Performance Improvement of CapsNet Over CNN

5. Conclusion

This work aimed to develop the next generation of CapsNet models to enhance white blood cell categorisation, therefore enabling accurate medical diagnosis. Showing superior accuracy, precision, memory, and F1-score, the research revealed CapsNets are much better than conventional Convolutional Neural Networks (CNNs). With a remarkable diagnostic accuracy of 94.5%, CapNet models exceeded CNNs in 5.5% increase. In medical settings, where accurately spotting white blood cells may enable physicians to create better treatment regimens and make better judgements, this improvement is rather crucial. With accuracy and sensitivity, the CapsNet model also performed quite well beating CNNs by 4.2% and 5.3%, respectively. Important components of medical diagnosis and directly affect patient care, these developments reduce the possibility of obtaining false positives and negatives. Fewer false positives translate into less therapies required that can endanger the patient or result in too costly expenses. Less false negatives, on the other hand, ensure that illnesses aren't overlooked, thereby enhancing patient outcomes via rapid actions. Moreover, the error analysis revealed that CapsNet had a reduced incidence of misunderstanding, which is another evidence of its strength and dependability for clinical use. When it comes to difficult medical jobs like blood cell analysis, these models really shine. This isn't always the case with older models. These results have huge effects, and they show that adding CapsNet to clinical diagnostic processes could completely change the way medical tests are done. CapsNet models help personalised medicine move forward and improve the quality of healthcare services generally by making blood cell classification more accurate and reliable. This shows how machine learning innovations can change medical diagnosis.

References

[1] Kanavos, A.; Papadimitriou, O.; Al-Hussaeni, K.; Maragoudakis, M.; Karamitsos, I. Advanced Convolutional Neural Networks for Precise White Blood Cell Subtype Classification in Medical Diagnostics. Electronics 2024, 13, 2818.

[2] Yao, X.; Sun, K.; Bu, X.; Zhao, C.; Jin, Y. Classification of white blood cells using weighted optimized deformable convolutional neural networks. Artif. Cells Nanomed. Biotechnol. 2021, 49, 147–155.

[3] Khan, A.; Eker, A.; Chefranov, A.G.; Demirel, H. White blood cell type identification using multi-layer convolutional features with an extreme-learning machine. Biomed. Signal Process. Control 2021, 69, 102932.

[4] Çınar, A.; Tuncer, S.A. Classification of lymphocytes, monocytes, eosinophils, and neutrophils on white blood cells using hybrid Alexnet-GoogleNet-SVM. SN Appl. Sci. 2021, 3, 503.

[5] Özyurt, F. A fused CNN model for WBC detection with MRMR feature selection and extreme learning machine. Soft Comput. 2020, 24, 8163–8172.

[6] Patil, A.; Patil, M.; Birajdar, G. White blood cells image classification using deep learning with canonical correlation analysis. Irbm 2021, 42, 378–389.

[7] N. J. Zade, N. P. Lanke, B. S. Madan, N. P. Katariya, P. Ghutke, and P. Khobragade, "Neural Architecture Search: Automating the Design of Convolutional Models for Scalability," PanamericanMathematical Journal, vol. 34, no. 4, pp. 178-193, Dec. 2024. https://doi.org/10.52783/pmj.v34.i4.1877

[8] Baghel, N.; Verma, U.; Nagwanshi, K.K. WBCs-Net: Type identification of white blood cells using convolutional neural network. Multim. Tools Appl. 2022, 81, 42131–42147.

[9] Bayat, N.; Davey, D.D.; Coathup, M.; Park, J. White Blood Cell Classification Using Multi-Attention Data Augmentation and Regularization. Big Data Cogn. Comput. 2022, 6, 122.

[10] Dong, N.; Feng, Q.; Chang, J.; Mai, X. White blood cell classification based on a novel ensemble convolutional neural network framework. J. Supercomput. 2024, 80, 249–270.

[11] Ali, M.A.; Dornaika, F.; Arganda-Carreras, I. White Blood Cell Classification: Convolutional Neural Network (CNN) and Vision Transformer (ViT) under Medical Microscope. Algorithms 2023, 16, 525.

[12] Ganesan, P.; Ramesh, G.P.; Puttamdappa, C.; Anuradha, Y. A Modified Bio-Inspired Optimizer with Capsule Network for Diagnosis of Alzheimer Disease. Appl. Sci. 2024, 14, 6798.

[13] Chui, K.T.; Gupta, B.B.; Alhalabi, W.; Alzahrani, F.S. An MRI scans-based Alzheimer's disease detection via convolutional neural network and transfer learning. Diagnostics 2022, 12, 1531.

[14] El-Sappagh, S.; Saleh, H.; Ali, F.; Amer, E.; Abuhmed, T. Two-stage deep learning model for Alzheimer's disease detection and prediction of the mild cognitive impairment time. Neural Comput. Appl. 2022, 34, 14487–14509.

[15] Garg, N.; Choudhry, M.S.; Bodade, R.M. A review on Alzheimer's disease classification from normal controls and mild cognitive impairment using structural MR images. J. Neurosci. Methods 2023, 384, 109745.

[16] El-Sappagh, S.; Ali, F.; Abuhmed, T.; Singh, J.; Alonso, J.M. Automatic detection of Alzheimer's disease progression: An efficient information fusion approach with heterogeneous ensemble classifiers. Neurocomputing 2022, 512, 203–224.

[17] Ye, H.; Zhu, Q.; Yao, Y.; Jin, Y.; Zhang, D. Pairwise feature-based generative adversarial network for incomplete multi-modal alzheimer's disease diagnosis. Vis. Comput. 2023, 39, 2235–2244.

[18] Mohi ud din dar, G.; Bhagat, A.; Ansarullah, S.I.; Othman, M.T.B.; Hamid, Y.; Alkahtani, H.K.; Ullah, I.; Hamam, H. A novel framework for classification of different Alzheimer's disease stages using CNN model. Electronics 2023, 12, 469.