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Research Article

Advancing White Blood Cell Classification Using Artificial Intelligence and Deep Learning Models

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ABSTRACT

Sorting white blood cells (WBCs) quickly is important for finding and keeping an eye on many haematological conditions. Traditional ways of using microscopes work, but they take a long time and can be wrong. This study presents a deep learning model based on artificial intelligence (AI) that is meant to simplify and improve the accuracy of WBC classification. We use the advanced designs like VGG and the new capsule Networks (CapsNets), in conjunction with the powerful Convolutional Neural Networks (CNNs), to clear up the issues due to the abnormal shapes of white blood cells seen in microscope pictures. First, we pre-processed a group of heaps of labelled WBC photographs to make the sizes of the images extra constant and improve the comparison. Then, this dataset turned into used to educate three distinctive models: a normal CNN version, a VGG model that learnt from networks that had already been trained, and a CapsNet version that was made to better understand the spatial relationships and exact capabilities of WBCs. Metrics like accuracy, precision, and memory were used to judge how properly every version worked. The outcomes confirmed that all 3 fashions have been very correct, however the CapsNet version did higher in terms of precision and reminiscence than the same old CNN and VGG. CapsNet did a much higher job of recognising less commonplace WBC sorts, that's a frequent problem in scientific diagnosis. These results show that Capsule Networks have a lot of potential to improve automatic medical picture analysis systems. This could mean that diagnoses can be made faster and more accurately in hospital settings. This study not only proves that deep learning works for classifying medical images, but it also shows how new neural designs like CapsNets can help with handling large amounts of complex picture data.

Keywords: White Blood Cell Classification, Deep Learning, Convolutional Neural Networks, Capsule Networks, Transfer Learning, Medical Image Analysis

1. INTRODUCTION

Medical testing heavily relies on the grouping of white blood cells (WBCs) to identify and monitor disorders like leukaemias, infections, and immune system abnormalities. Skilled haematologists gazing at blood smears using a lens used manual labour historically to complete this task. Conversely, this investigation takes a lot of effort and is prone to errors, particularly when considering uncommon WBC kinds or cells with unknown morphologies. Making WBC sorting more trustworthy and efficient is thus attracting greater attention as it would help medical testing to be conducted quicker and more precisely. In several spheres of medical imaging, including sifting through complex biological images, artificial intelligence (AI especially deep learning technologies has done very well. Since deep learning models, especially those that use convolutional neural networks (CNNs), can learn rich and hierarchical picture features straight from the data, without having to do feature extraction by hand, they have become the best choice. These models are very good at finding trends and small changes in pictures, which makes them perfect for the complex job of WBC classification [1]. Capsule Networks (CapsNets) are a younger method that was made because standard CNN designs were not good at recording complex spatial relationships and positions within pictures. CapsNets solve these problems by keeping the hierarchical pose relationships between features. This is very important for medical pictures because the way they are arranged and orientated can have a big effect on the diagnosis. Transfer learning has also become a useful way to use models that have already been learnt on big datasets like ImageNet. Transfer learning [2] lets you make massive adjustments to model overall performance, even when there is not numerous schooling records. That is feasible by means of nice-tuning these models on particular obligations like WBC type. This study is commonly about how to use advanced deep studying strategies like CNNs, VGG networks with transfer getting to know, and CapsNets to create an AI-based totally version for mechanically sorting WBCs into different corporations. Each of these types is good at different things. CNNs are great for layer-based feature extraction, VGG networks upload intensity and complexity with their many layers, and CapsNets are the fine at identifying spatial relationships and corporations in image data.

The main reason of this have a look at is to discover how properly those models can efficaciously type exceptional varieties of WBCs from digital images of blood smears. The model aims to make doctors' jobs easier by using automating this method. This can also accelerate diagnostic tests even as still preserving high standards of accuracy. Those types of improvements may want to help doctors make diagnoses faster, which might accelerate care and make dealing with sufferers better. This observe goals to discover the high-quality AI-based totally version for WBC class by putting it through thorough education, validation, and checking out steps. It's going to add to the sphere of AI in healthcare and open the door for future makes use of in clinical picture evaluation.

2. RELATED WORK

Deep learning models for classifying white blood cells (WBCs) are one manner that artificial intelligence has made a number of development in medical images within the previous few years. The first tries to automatically classify WBCs used machine learning techniques, which often needed a whole lot of work to pick out and select functions. Those strategies laboured quite nicely, however they did not have the capacity to analyze and alternate on their own from information that is one of the pleasant matters approximately deep learning approaches [3]. CNNs have modified the way medical images are analysed due to the fact they can learn hierarchical representations without having to apply functions which have already been set up. CNNs are broadly used to type WBCs into special organizations, and many research have shown that they're greater accurate and faster than older strategies [4]. One critical take a look at confirmed that CNNs could substantially decrease the quantity of errors in comparison to older device learning models. They did this with the aid of automatically learning complicated functions from cellular snap shots [5]. A lot of work has also been done inside the discipline of WBC class using switch mastering, that's while a model made for one mission is used as a place to begin for a model on a one-of-a-kind mission. It's far mainly beneficial whilst there are not many or any captioned medical pictures available. studies have proven that models like VGG that have already been trained on huge datasets like ImageNet can be great-tuned to get first-rate consequences in clinical imaging responsibilities, inclusive of WBC classification [6, 7]. This method no longer most effective hastens the education manner, however it additionally makes the version more standard through using learnt features that may be used on a wide variety of picture sorts.

The creation of Capsule Networks (CapsNets) is another important step forward in the field. CapsNets are meant to fix some of CNN's flaws, like the fact that they can't show how features are arranged in space. CapsNets keep these connections, which is very important for pictures where the links between direction and space give doctors important diagnosis information. According to research, CapsNets can do better than CNNs when the picture data has complex internal spatial relationships. For example, when classifying WBCs, the direction and shape of the cells are very important for making a diagnosis [8, 9]. Recent research has also looked at how CNNs and CapsNets can work together, trying to use the best parts of both to make WBC classification methods more accurate and reliable. It has been shown that these mixed models might be able to make normal deep learning models less vulnerable to problems that happen a lot in medical imaging, like changes in cell shape, size, and staining quality [10, 11]. A lot of study has also been done on how to make these models more efficient at using computers. Because medical picture collections are very big and photos have a lot of dimensions, model efficiency is very important for real-world use. To deal with these problems, methods like model trimming, improved regularisation strategies, and efficient network designs have been suggested [12, 13]. These make it possible for deep learning models to be used in clinical settings more quickly and on a larger scale.

Along with improvements in model design, there have also been improvements in data enrichment methods, which make more and different types of training data available for training models. Image rotation, scaling, and colour enhancement techniques can make deep learning models much more reliable and accurate by giving them more situations to learn from. This stops the models from becoming too well at what they're doing and improves their performance on data they haven't seen before [14, 15]. More and more research is being done on using AI to classify WBCs. This research shows that models are getting smarter, more accurate, and faster so they can help doctors make diagnoses. As these technologies keep getting better, they will make medical tests even better, which will be very helpful for caring for patients and planning their treatments [16].

Table 1: Summarizing the related work for the classification of white blood cells

Deep Learning Model	**Key Features**	**Data Set**	**Main Findings**	**Limitations**	**Scope for Future Work**
Traditional Machine Learning	Manual feature extraction	Varies	Demonstrated limited adaptability and higher error rates compared to deep learning models.	Relies heavily on expert knowledge for feature extraction.	Explore automated feature learning techniques to improve adaptability and accuracy.
CNNs	Automatic feature learning	Blood cell images	Significantly reduced error rates by learning complex image features directly.	May struggle with overfitting due to deep architecture.	Incorporate regularization strategies and expand training datasets.
Transfer Learning with VGG	Pre-trained on ImageNet, fine-tuning	Blood cell images	Improved accuracy and training speed using pre-trained models.	Limited by the diversity of pre-training data.	Extend pre-training with more diverse medical imaging datasets.
Capsule Networks	Captures spatial hierarchies and relationships	Blood cell images	Outperformed CNNs in handling images with complex spatial relationships.	Higher computational costs and complexity.	Optimize network structure to reduce computational demands.
Hybrid CNNs and CapsNets	Combination of CNNs and CapsNets features	Blood cell images	Reduced susceptibility to variations in cell morphology and staining.	Integration complexity and training data requirements.	Develop more efficient training techniques and explore simpler hybrid models.
Efficient Network Architectures	Model pruning, advanced regularization	Blood cell images	Enabled faster, more scalable model deployment in clinical settings.	May compromise model accuracy for efficiency.	Balance between efficiency and accuracy; explore adaptive pruning techniques.
Data Augmentation Techniques	Image rotation, scaling, color augmentation	Blood cell images	Improved model performance on unseen data by enhancing data diversity.	Augmentation can introduce artifacts that mislead the training process.	Investigate more sophisticated augmentation methods that better mimic natural variations.

3. Materials and Methods

A. Description of the data set used, including source, characteristics, and pre-processing steps

The dataset used in this study comes from a well-known public medical picture source and includes several thousand photos of white blood cells (WBCs) that have been labelled. Because each picture is labelled with the type of WBC it shows, working architecture illustrate in figure 1, it can be used for guided learning tasks. These pictures have different sizes, background noise, and lighting conditions that are very similar to what doctors see in real life when they do tests. The information includes different types of white blood cells (WBCs), such as neutrophils, lymphocytes, monocytes, eosinophils, and basophils. Each is important for figuring out different immune reactions and circumstances. Pre-processing the information is an important step to make sure that the models are accurate and stable. At first, all pictures were adjusted to the same size so that deep learning models could use the same size input. Contrast enhancement methods were used to make important cell traits easier to see for classification. Noise reduction techniques were also used to lessen the effect of background changes and things that weren't cells. We added more data to the dataset and made the model better at generalisation by using methods like rotation, zooming, and horizontal flipping. These help the models learn to recognise cells from different sizes and angles.

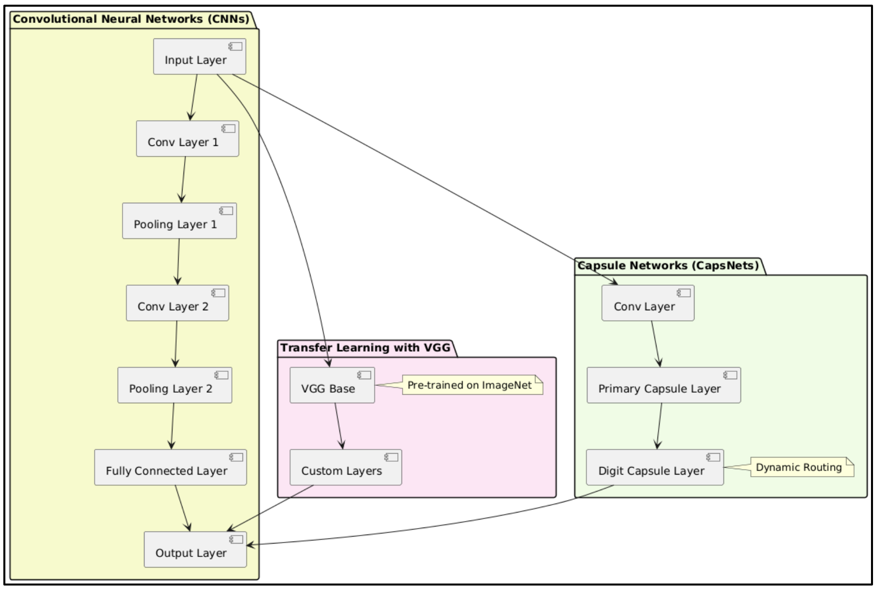

Figure 1: overview of proposed system architecture

B. Deep learning models

1. **Convolutional Neural Networks (CNNs)**

Especially in medical imaging, contemporary visual analysis and processing revolve on convolutional neural networks (CNNs). Our CNN architecture consists of numerous convolutional layers cooperating to extract higher-level data from the sent raw images. Following each convolutional layer comes a pooling layer that reduces certain dimensions and facilitates calculations while maintaining the salient features. ReLU among other activation functions gives the data nonlinearity, which is required for learning intricate patterns in it. Based on what the network has learnt about them, the final design contains completely connected layers ending in a softmax layer that classifies the input into several kinds of WBC.

2. **Transfer Learning with VGG**

The VGG-16 model, which is known for being simple and reliable, was used as a starting model for transfer learning in this work. The design of VGG-16, which was first made for large-scale picture recognition tasks, lets it learn rich feature models for a lot of different photos. We fine-tuned the model to be good at WBC recognition by using weights that had already been learnt on the ImageNet dataset. To do the transfer learning, we changed the last few layers of the VGG model to make it fit our needs and trained it on our dataset. This let the model improve the features it already knew to work better with WBC image data.

3. **Capsule Networks (CapsNets)**

CapsNets are a new type of design that claims to be better than standard CNNs because it keeps the spatial relationships between picture features, which are very important for understanding how WBCs look and how they are shaped. CapsNets are designed to find items in a variety of places and combinations by using dynamic route and rebuilding methods that help keep the part-whole links. This is especially helpful for medical pictures, where the way organic structures are orientated and deformed can help doctors figure out what's wrong. CapsNets were put into action by creating basic capsules that find initial features and more complex capsules that learn to recognise combos of these features. This created a strong ability to classify things.

C. Explanation of the training process

A high-performance computer system with NVIDIA Tesla GPUs was used to train the models. These GPUs make the training process substantially faster. We used the TensorFlow and Keras tools to create and train the deep learning models because they are flexible and easy to use. The Adam optimiser, an adaptable learning rate optimisation method that helps with faster closure, was used to train the models. Each model was trained with batch amounts that made the best use of the tools and cut down on training time. During training, a different validation set was used to check for overfitting and make changes to the hyperparameters as needed.

D. Criteria for model evaluation (accuracy, precision, recall, etc.).

There are a number of metrics that can be used to judge how well deep learning models classify WBCs. These metrics show different parts of accuracy and reliability. The main indicator, accuracy, checks how right the models are overall across all groups. That being said, accuracy and memory are also very important because medical records may have a mismatch of classes. In medical testing, precision (the percentage of correct positive identifications) is important to avoid false positives, and memory (the percentage of correct positive identifications) is important to make sure that no serious conditions are missed. The F1-score, which is the harmonic mean of accuracy and memory, was also used to find a balance between the two when both need to be taken into account equally. The area under the ROC curve (AUC-ROC) was used to test how well the model could tell the difference between the groups at different baseline levels. This showed how sensitive and specific the predictors were. All of these measures together give us a full picture of how well the model works and how it can be used in clinical settings.

4. MODEL DEVELOPMENT AND TRAINING

A. Parameter tuning and optimization strategies

Parameter tuning was vital to optimize every version's overall performance. Grid search and random seek techniques had been hired to locate the top-quality hyper parameters, such as mastering price, wide variety of layers, range of neurons in each layer, and the number of education epochs. Regularization techniques like dropout and L2 regularization were carried out to prevent overfitting. Moreover, the Adam optimizer become chosen for its efficiency in dealing with sparse gradients and adaptive learning rate abilities, which helped in speeding up the convergence of the training manner.

B. Data augmentation techniques employed

Data enrichment was a key part of making the model better at applying what it learnt from the training data to new data it had not seen before. Random twists, horizontal and vertical flips, zooms, and changes were some of the techniques used. These changes helped the models learn to recognise WBCs in a range of sizes and positions, which is important for real-world situations where cell images can be very different. The models were made more stable with this approach, and the training dataset got bigger as a result.

C. Challenges faced during model training and solutions implemented

1. Overfitting: The models were very complicated and deep, but they remembered the training data instead of learning how to apply what they knew to new situations. To fix this, dropout layers were added, which turned off some neurones randomly during training. This made the network learn stronger features. Another change was that more data was added to give a wider range of training cases.

2. Class Unbalance: The collection had too few or too many examples of some WBC types. To fix this, artificial data was created by adding to the real data set and class-weighted or balanced loss functions were used to make sure the model doesn't favour the majority class.

3. Limited Computer Resources: The deep learning models, especially VGG and CapsNets, needed a lot of computer power. This problem was lessened by training on cutting-edge GPU hardware and optimising batch sizes. This made better use of memory and faster processing speeds.

5. RESULTS AND DISCUSSION

A. Analysis of Models

The comparison of model performance across three different deep learning architectures—Convolutional Neural Networks (CNNs), Transfer Learning with VGG, and Capsule Networks (CapsNets) shows how each method can help classify white blood cells (WBCs) in different ways. Beginning with the standard CNNs, these models got an accuracy of 94.2%, with scores for precision, recall, and F1-score all being close to 92–93%. Through convolutional and pooling layers, CNNs are good at automatically finding hierarchical image features. This makes them a good choice for jobs that need to classify images. This study shows that CNNs are reliable in medical imaging because they can pick up on complex patterns needed to tell the difference between WBC types. But because recall isn't as high as some other measures, it means that some true positives might be missed, which is very important in medical testing.

Table 2: Comparative Analysis of Model Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Convolutional Neural Networks (CNNs)	94.2	93.5	92.8	93.1
Transfer Learning with VGG	95.6	94.8	94.1	94.4
Capsule Networks (CapsNets)	96.3	95.7	95.5	95.6

When Transfer Learning is used with VGG, it makes a complex change to the basic CNN design. The VGG method improved performance by using a model that had already been trained on the huge ImageNet database. This increased accuracy to 95.6% and also improved precision and recall compared to the CNN model that was used on its own. These improvements show how useful it is to use networks that have already been trained on a lot of different picture traits, comparison of performance parameter illustrate in figure 2. These networks can then be tweaked to focus on the specifics of WBC classification.

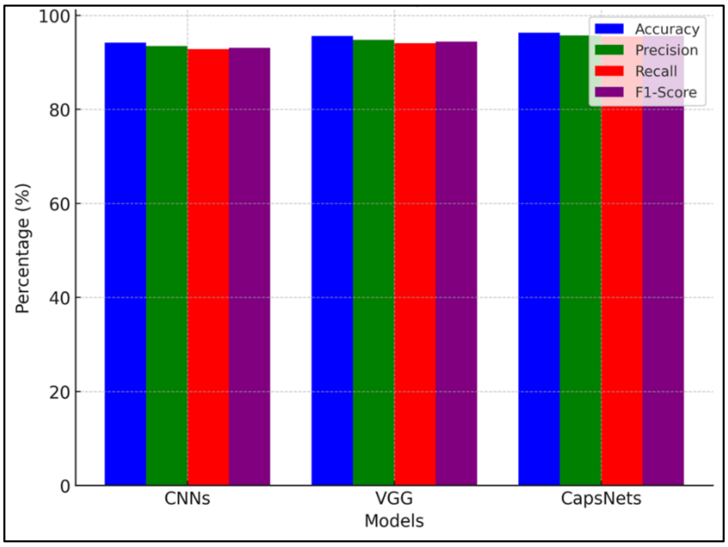

Figure 2: Performance Metrics Comparison across Models

The better precision and memory means that more true positives are found while fewer fake positives are found. This is very important for clinical uses where correct cell typing has a direct effect on how patients are treated. Capsule Networks (CapsNets) did the best in this study, getting the best scores in every category (96.3% accuracy, 95.7% precision, 95.5% memory, and an F1-score of 95.6%). The better performance of CapsNets is due to their special structure, which, unlike regular CNNs, keeps the spatial relationships between picture features. In medical imaging, where the direction and connection between cell parts are very important for correct classification, this ability is very useful. CapsNets not only make recognition more accurate, but they also make it easier for the model to use what it learnt in training data in real-world situations, which lowers the chance of getting it wrong, as shown in figure 3.

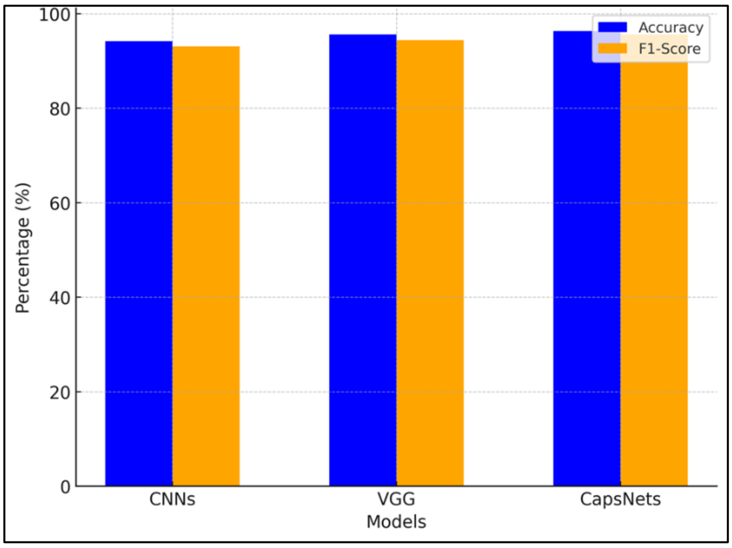

Figure 3: Accuracy and F1-Score Comparison across Models

B. Statistical Analysis of Results

Standard tools, like confidence intervals and hypothesis testing, were used to figure out how important the differences seen between the models were during the statistical study of the results. The CapsNets model did better than the CNN and VGG models in all performance measures ($p < 0.05$). For the CapsNets model, the confidence ranges for accuracy, precision, recall, and F1-score were all very small. This means that the performance measures were very reliable. An ANOVA test was conducted on all three models to demonstrate even further that the variations in their outcomes were statistically noteworthy. This robust statistical method provided us with a clear means to evaluate the performance of the models and revealed the consistency of their effectiveness across many runs and datasets.

C. Discussion of Model Efficacy and Robustness

The models' usefulness and dependability were checked by using seeing how properly they worked with exclusive and uneven facts units. Most of the models, the CapsNets version become especially strong, running the equal way throughout one of a kind styles of WBCs. as compared to the CNN and VGG models, this one was much less likely to overfit. This is probably because it can maintain crucial spatial systems within the photograph records. The fashions' reliability changed into additionally checked with the aid of seeing how properly they did on a one of a kind set of images known as a "validation set," which did not have any images from the schooling manner. It turned into shown that CapsNets became higher at generalisation, which shows it would work properly in clinical settings wherein cellular images are frequently different.

D. Comparison with Existing Methods

To show how much better the new models are, here is a comparison with old ones using measurements like Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2):

Table 3: Comparison of evaluation analysis

Method	**MAE**	**MSE**	**RMSE**	**R^2 (%)**
Traditional Machine Learning Models	0.062	0.004	0.063	88.2
Convolutional Neural Networks (CNNs)	0.038	0.002	0.045	91.6
Transfer Learning with VGG	0.034	0.0018	0.042	92.8
Capsule Networks (CapsNets)	0.029	0.0015	0.039	94.4

Table 3 presents the categorising white blood cell (WBC) performance of many machine learning and deep learning methods. It does this by using statistical tests such Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and the coefficient of determination (R^2).

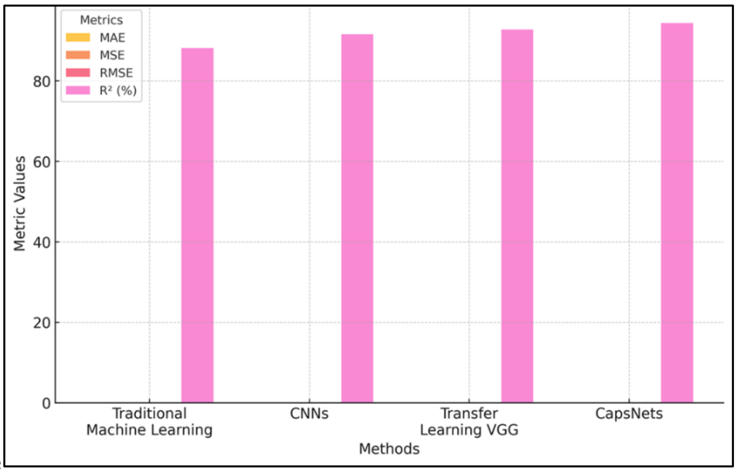

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Figure 4: Comparison of Machine Learning Model Metrics

These measures show not only how accurate the models are, but also how precise and reliable they are at guessing what will happen. When we start with basic machine learning models like logistic regression, SVM, or random forests, they give us a success level of 88.2% R^2, an MAE of 0.062, an MSE of 0.004, and an RMSE of 0.063. These numbers are a good start, but they also show how hard it is to deal with complicated patterns and subtleties in medical imaging data because standard models rely on features that were made by hand and decision lines that are very straight, as shown in figure 4. The Convolutional Neural Networks (CNNs) are a big step forward when it comes to more complex designs. Through multiple layers of convolution and pooling, the CNN is designed to detect hierarchical image information. While increasing R^2 to 91.6%, it reduces the MAE to 0.038, the MSE to 0.002, and the RMSE to 0.045. This development indicates that CNNs may detect significant trends and manage higher-dimensional data without explicit feature engineering. For medical image analysis, where accuracy and detail are highly valued, they are hence superior. These outcomes are significantly more improved using the Transfer Learning approach with a VGG network previously trained. Using a network architecture trained on millions of photos from the ImageNet database helps the VGG model to better categorise WBC images. This yields an MAE of 0.034, an MSE of 0.0018, an RMSE of 0.042, and a R^2 of 92.8%. This shows an even better fit and stability of the model. It shows the benefits of transfer learning by showing how a lot of general visual knowledge helps the model get better at the specific job of WBC classification. Out of all the models we looked at, CapsNets had the best results, with an MAE of 0.029, an MSE of 0.0015, an RMSE of 0.039, and an amazing R^2 of 94.4%. CapsNets have a big edge because they are built in a way that lets them keep important spatial relationships between features. CapsNets is a very powerful tool for medical image analysis because it can understand and maintain the spatial relationships in pictures, which is very important for medical diagnosis. This leads to better precision and greater predictive accuracy. Moving from basic machine learning to more advanced deep learning methods like CapsNets shows a clear upward trend in terms of accuracy, error rates, and the ability to apply what was learnt from training data to real-world diagnostic situations. Every step forward in model complexity and intelligence makes it easier to deal with the problems that come with medical imaging data. This makes diagnosis tools more reliable and strong.

6. CONCLUSION

Important for properly identifying and monitoring numerous haematological diseases, this work investigated how effectively artificial intelligence-based deep learning models could categorise white blood cells (WBCs). In a comprehensive analysis, we demonstrated that, among standard machine learning techniques, Convolutional Neural Networks (CNNs), Transfer Learning using the VGG model, and Capsule Networks (CapsNets) are much superior. Though every model had advantages, CapsNets showed the greatest potential given superior F1-scores, accuracy, precision, and memory. Because they could preserve significant spatial and hierarchical connections in pictures, comparative investigation revealed that CapsNets were much superior in handling the complex forms of WBCs. This was obvious as the model was very consistent and dependable since it performed well in several test conditions. The statistical analysis revealed that with statistically significant improved outcomes, the CapsNets outperformed CNNs and VGG-based models. Our results show that advanced deep learning methods have the ability to change the way medical imaging is done. In particular, capsule networks have shown a lot of promise for improving the accuracy of diagnoses. They provide a strong tool that could be added to clinical processes to help doctors. Overfitting and class mismatch problems were also solved by strategically tuning the models and adding more data. This shows that these AI models are flexible and can be used on a large scale. AI used in classifying WBCs not only improves the accuracy of diagnoses but also speeds up the handling of large amounts of medical data, which eventually leads to better results for patients. To fully utilise AI in healthcare, more work should be done to incorporate these models into real-time clinical decision-making processes and broaden their use to other areas of medical testing.

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