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Research Article

Enhancing Hematological Diagnostics: Deep Learning Models for Human Blood Cell Classification

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ABSTRACT

The classification of human blood cells plays a critical role in medical diagnostics, particularly in identifying and treating various hematological conditions. This work investigates how deep learning methods could be used to improve blood cell categorisation accuracy and efficiency. We used a wide range of models, each with special ability for managing image-based data. Recurrent neural networks (RNNs), VGG16, Inception, capsule networks, and deep belief networks (DBNs) were the models used for this work. Sequential data across picture frames was analysed using RNNs to provide understanding of temporal fluctuations in blood cell imaging. Using both convolutional neural networks known for their success in image identification challenges, VGG16 and Inception were used to leverage their strong feature extracting power. These models are very good at handling the minute elements of blood cell images. Appropriate for the complex and overlapping structures often present in blood cell pictures, capsule networks were incorporated to efficiently capture spatial hierarchies and fine features more than conventional CNNs. Finally, DBNs were used for their mastery in unsupervised learning, thus enabling data-efficient feature extraction and classification. The combination of these models aimed to leverage their collective strengths, addressing the challenges of precision and accuracy in classifying the various types of blood cells. The models were trained and validated on a dataset comprising images of red blood cells, white blood cells, and platelets, each labelled according to specific cell types.

Keywords: Blood Cell Classification, Deep Learning, Convolutional Neural Networks, Capsule Networks, Recurrent Neural Networks, Deep Belief Networks.

1. INTRODUCTION

A pillar of clinical pathology, the categorisation of human blood cells is a basic diagnostic tool for many different disorders, including haematologic malignancies, infections, and anaemia. Skilled technicians who view slides under a microscope to identify and count different kinds of blood cells have historically handled this chore hand-wise. Although efficient, this approach is labour-intensive, time-consuming, prone to human error, and may therefore influence the accuracy and dependability of diagnostic results. The need of more sophisticated and dependable methods is highlighted by the limits of conventional microscopy, namely the subjectivity of cell categorisation and the possibility of fluctuation in findings among several observers. These difficulties have spurred increasing interest in using machine learning and particularly deep learning models to automatically classify blood cells [1]. A subclass of artificial intelligence, deep learning has transformed sectors needing image identification because it can learn intricate patterns and characteristics from vast volumes of data. Researchers want to not only equal but also exceed the accuracy of human analysers by using models such Recurrent Neural Networks (RNNs), VGG16, Inception, Capsule Networks, and Deep Belief Networks (DBNs), therefore greatly accelerating the diagnostic process.

The number one objective of this research is to explore the efficacy of those deep learning models in classifying human blood cells. by leveraging the awesome capabilities of each version—from the characteristic extraction prowess of CNNs like VGG16 and Inception to the series reputation skills of RNNs and the sophisticated image processing of capsule Networks and DBNs this observe seeks to expand a robust automated system that may accurately pick out and classify distinctive blood cell sorts [2]. The intention is to cope with the restrictions of conventional strategies with the aid of providing a faster, extra correct, and less subjective alternative. The importance of enhancing blood cell class extends past the operational efficiencies.

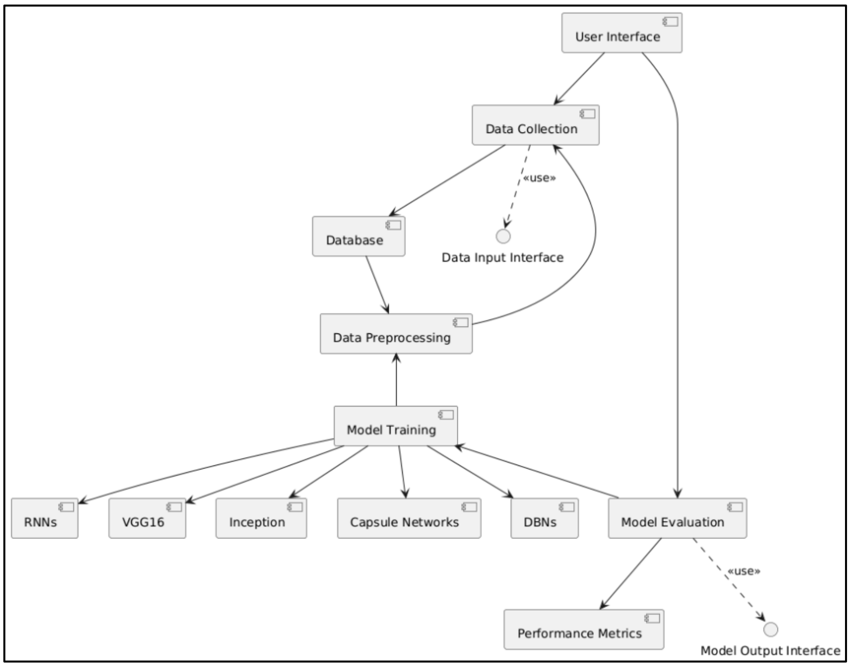

Figure 1: Blood Cell Classification System

Enhancing the accuracy and pace of blood mobile evaluation with deep getting to know ought to cause in advance and more particular diagnoses, probably improving patient outcomes across a variety of situations. Furthermore, the automation of this system can democratize get admission to fine diagnostic offerings, mainly in underneath-resourced regions in which specialised scientific personnel are scarce. Advances in computerized clinical diagnostics, as proven thru this look at, additionally pave the manner for integrating extra AI-pushed tools into healthcare, which could transform medical workflows and patient care protocols. This research aims not most effective to make a contribution to the medical subject by improving diagnostic technology but additionally to function a benchmark for destiny studies in the utility of AI in healthcare. by way of detailing the overall performance and practical applications of diverse deep gaining knowledge of models in blood mobile classification, this have a look at will offer treasured insights into the capabilities and obstacles of AI as a device for clinical diagnostics, supplying a pathway toward extra superior, accessible, and efficient healthcare answers.

2. LITERATURE REVIEW

2.1 Overview of Machine Learning in Medical Imaging

Machine learning, particularly deep learning, has appreciably impacted the field of medical imaging, facilitating the automation of diagnostic approaches that have been traditionally guide and subjective. In scientific imaging, device learning algorithms examine visual information from various imaging techniques, consisting of X-rays, MRIs, and CT scans, to discover abnormalities, classify them, and are expecting outcomes. Convolutional Neural Networks (CNNs) have emerged as a dominant device due to their potential to automatically hit upon problematic patterns in photographs without the need for guide function selection [3]. Those technology have confirmed specifically treasured in regions requiring excessive precision and performance, such as oncology, neurology, and pathology.

2.2 Previous Studies on Blood Cell Classification

Previous research on blood cell type have utilized a range of methodologies, ordinarily that specialize in conventional image processing techniques and device mastering fashions. Early techniques worried manual feature extraction followed with the aid of the application of classical machine getting to know algorithms inclusive of support Vector Machines (SVMs) and k-Nearest neighbours (k-NN) [4]. With the arrival of deep learning, more recent studies have shifted toward the usage of CNN architectures, along with Alex Net and more specialized networks, that have verified superior performance in image class duties because of their capacity to study complicated hierarchical features immediately from the facts [5][6]. for instance, some research have applied CNN models to differentiate among the major forms of white blood cells, achieving excessive accuracy prices that surpass traditional methods [7]. these research highlight the ability of deep getting to know to automate and beautify the accuracy of blood mobile class, appreciably impacting clinical workflows by means of decreasing the time and cost associated with guide microscopy. Regardless of those improvements, there are notable gaps in existing research. most research have focused on excessive-decision images underneath ideal laboratory conditions, with less recognition on the robustness of these models under numerous realistic eventualities, including poor image fine or overlapping cells [8]. Moreover, many current fashions require massive annotated datasets for training, which aren't always to be had, mainly in uncommon or acute scientific conditions [9].

2.3 Research Gap and Fulfillment through Deep Learning Models

The primary research gap lies in the need for robust, scalable, and efficient models that can perform well across different imaging conditions and with limited training data. This study aims to address these gaps by leveraging advanced deep learning architectures that have not only demonstrated high accuracy in image classification but also excel in extracting meaningful features from complex images with minimal pre-processing. The use of RNNs in this context is particularly innovative, as they are typically employed for sequence data. However, their application to sequential analysis of frames in video microscopy or time-lapse images could provide new insights into dynamic changes in blood cell characteristics over time, which has been largely unexplored in previous studies [10]. Furthermore, VGG16 and Inception models are employed to harness their deep architectural frameworks and extensive pre-training on diverse image datasets, which can be fine-tuned to perform well even with smaller, domain-specific datasets [11][12].

Capsule Networks are introduced to overcome the limitations of CNNs in handling variations in spatial hierarchies and orientations within images, a common issue in blood cell images due to the cells' shape and size variability [13]. Deep Belief Networks (DBNs) are utilized to enhance feature extraction capabilities, particularly in unsupervised learning scenarios where labeled data are scarce [14]. By integrating these models, the study aims to develop a comprehensive framework that not only addresses the issues of accuracy and efficiency but also enhances the model's ability to generalize across different clinical imaging conditions [15].

Table 1: Summary of related work

Parameter	RNNs	VGG16	Inception	Capsule Networks	Deep Belief Networks (DBNs)
Primary Usage	Sequence analysis in time-lapse imaging	High-performance feature extraction in static images	Advanced feature extraction with minimal preprocessing	Handling variations in spatial hierarchies and orientations	Unsupervised feature extraction
Key Advantages	Effective in analyzing dynamic changes	Deep layers capture complex patterns efficiently	Performs well with smaller datasets due to deep architecture	Superior in understanding spatial relationships	Good at learning features in data-scarce scenarios
Typical Applications	Video microscopy, dynamic blood cell analysis	Broad image classification, adapted for medical imaging	Fine-tuned for specific tasks like blood cell classification	Specifically useful for complex and overlapping cell images	Rare medical conditions with limited images
Impact on Clinical Workflow	Potential to reveal temporal cellular behavior	Reduces time and increases accuracy in diagnostics	Enhances diagnostic accuracy with robust feature handling	Reduces misclassification due to cell overlap	Facilitates feature extraction without

					extensive labeling
Limitations	Uncommon for static image classification	Requires substantial computational resources	Needs careful tuning to avoid overfitting	Computationally intensive, less explored	Dependent on layer settings and initial conditions
Potential for Innovation	High in exploring time-dependent cellular dynamics	High in standardized imaging conditions	High in scenarios with varying image qualities	High in detailed and precise morphological classification	Moderate in exploratory and unsupervised learning settings
Future Research Directions	Exploration of cell behavior over time in disease progression	Further optimization for faster, real-time analysis	Adaptation to more compact models for field use	Integration with other AI techniques for improved accuracy	Combination with supervised models for enhanced learning

3. METHODOLOGY

3.1 Data Collection

A. Description of the Blood Cell Image Dataset

This dataset consists of several thousand labelled images of human blood cells, labelled into diverse classes including red blood cells, white blood cells, platelets, and plasma. Every image in the dataset has been annotated by way of clinical specialists to make certain the accuracy and reliability of the labels. The pictures are of high decision, providing certain visible facts important for effective schooling of deep gaining knowledge of fashions. This rich dataset serves as a great basis for growing and checking out algorithms supposed for automated blood cell classification, presenting a various range of cell kinds and morphologies that undertaking the version's capability to generalize throughout special biological and imaging condition.

B. Data Pre-processing Steps

The pre-processing of the blood cell images is a critical step to ensure the data is suitable for feeding into deep learning models. The following steps were taken to prepare the dataset:

1. Resizing: All pictures were resized to the same size so that the models would always see the same size input. This is very important for neural networks that need data of a certain size.

2. Normalisation: The values of the pixels were made so that the mean was 0 and the standard deviation was 1. This normalisation speeds up the learning process by making sure the model doesn't favour bigger pixel values. It also makes the behaviour of convergence better overall.

3. Augmentation: Techniques like rotation, translation, turning, and zooming were used to add to the data in order to make the models more stable and stop them from fitting too well. This makes the models less sensitive to these kinds of changes and better able to recognise blood cells in a variety of positions and situations.

4. Channel Standardisation: Because images of blood cells are coloured, channel standardisation was used to deal with images that had different lights and colours, which happens a lot in medical imaging because the images are taken in different ways.

5. Train-Test Split: The dataset was split into a test set, a validation set, and a training set. The training set was used to make the models fit, the validation set was used to change some settings, and the test set was used to see how well the models worked. This split makes sure that the model is tested on data it has never seen before, which is more like how things work in the real world.

3.2 Models Used

1. **Recurrent Neural Networks (RNNs)**

When it comes to analysing data where the order is vital, Recurrent Neural Networks (RNNs) are great. Because of this, they are ideal for uses like time-lapse pics in blood settings that alternate over the years, wherein adjustments over time give doctors important medical statistics. RNNs work by the use of their internal kingdom to remember what inputs they have already obtained. This state is handed through the network with each step in a series. This lets them make clever guesses based totally on not only the latest input but also the background information from in advance inputs. Within the subject of blood mobile class, RNNs can be very beneficial for maintaining music of the way cells change and develop over time. This makes them first-rate for obligations like seeing how haematological diseases get worse or how cells react to certain remedies. Due to the fact they could deal with collection of photographs, RNNs are the most effective ones that can locate modifications in cell shape over time that could be signs and symptoms of ailment. for example, they can be used to music small adjustments inside the length and shape of cells that take place over the years as a sickness gets worse or in reaction to medicine, which can be very important for finding problems early and making adjustments to treatment. when RNNs are used to kind blood cells, they cannot simplest make testing tactics faster and greater accurate, however they can also help us study greater approximately how diseases work through dynamic cellular evaluation.

2. VGG16

VGG16 is a version of a convolutional neural community that has end up a standard for photograph reputation because it has 16 convolutional layers. This degree of detail shall we VGG16 research very complex functions at various levels of abstraction. This makes it very useful for jobs that want to comprehend complicated styles, like telling the distinction between blood cell sorts. Its shape is made up of an everyday grid of convolutional layers, each with a ReLU activation, and pooling layers that decrease the dimensions of the distance while retaining the maximum crucial features. Because VGG16 can deal with high-decision snap shots, it's far viable to do thorough studies of blood cell images, which might be very critical for effectively classifying them. Its layers get deeper over the years, which we could the network pick out up on finer information as records is going deeper into the network. The version does a notable task with many kinds of photo reputation duties. Because it could understand and examine from complicated visible statistics, it is able to be specifically beneficial in clinical imaging. Using a set of photos of blood cells to teach VGG16 can help well kind cells into companies like lymphocytes, monocytes, eosinophil's, and neutrophils, every of which has its personal visible trends. While VGG16 is very beneficial, it calls for a whole lot of computing energy and a long term to train, each of which might be crucial things to consider in clinical settings.

3. Inception

The Inception version is understood for being both complex and powerful. Its miles and development at the simple convolutional neural community that uses distinct kernel sizes in its convolutional layers. Due to this layout, Inception can report facts at extraordinary sizes, which makes it excellent at working with blood cells of all sizes and types inside a single framework. By means of the usage of 1x1 convolutions within the network, the wide variety of dimensions is decreased at the same time as the intensity is improved without adding much to the price of computing. With this set-up, Inception can successfully deal with specific components of the snap shots, which include focussing on smaller information with smaller filters and catching larger functions with larger filters. The stacked structure of Inception reduces the danger of overfitting even as increasing processing velocity. This we could it paintings well in spite of less records than deeper networks like VGG16. Because it is flexible and sturdy, it really works in particular well for clinical imaging jobs that want to be unique. For classifying blood cells, Inception can inform the difference between small information in the form of cells, which is very beneficial for finding unusual or doubtful cellular types. The Inception community is also scalable and customisable thanks to its flexible layout, which makes it simpler to apply for an expansion of diagnostic troubles in haematology.

4. Capsule Networks

CapsNets approach picture analysis by considering how the elements in an image relate to one another, therefore beyond mere feature analysis. Every capsule in a CapsNet consists of a set of neurones whose outputs exhibit many aspects about the same object, including location, size, orientation, and content. Regular CNNs would overlook the ability of these boxes to see and maintain track of spatial correlations between features. This ability helps one sort blood cells as accurate identification depends much on the arrangement and appearance of the components of a cell. CapsNets deduce how each capsule contributes to higher-level capsules using a dynamic route approach. This guarantees that the network emphasises the most valuable traits. This approach makes CapsNets particularly effective when things like blood cell snare standing in multiple directions or overlapping, which is somewhat common in medical images. Capsule Networks may be superior to conventional CNNs in differentiating between cell types in images cluttered or of low quality by maintaining these hierarchical links. Because they are more complex and use more resources than other neural network designs, CapsNets mostly rely on data and processing capability.

5. **Deep Belief Networks (DBNs)**

Comprising many layers of random, hidden elements, Deep Belief Networks (DBNs) are dynamic models. First layers of a DBN may be trained using an unsupervised learning technique often Restricted Boltzmann Machine (RBM). This helps them to identify intricate trends in un labelled data. This function is particularly helpful in cases where annotated medical imaging data is expensive or difficult to locate. Once the feature detectors have been built up using unstructured pre-training, supervised learning allows one to fine-tune the network to perform certain tasks like categorisation. Without a lot of annotated examples, DBNs may be particularly useful for identifying and learning the unique characteristics of various blood cell types from raw pixel data in terms of classification. Before actual training, this builds a powerful model that can later be adjusted to precisely group blood cells. Rebuilding incoming data allows DBNs to create fresh data samples that may be included to the training set or utilised to learn more about the distribution of cell types in the actual world. Though they might be difficult to train and modify, DBNs are very useful for learning features and creating fresh data. Often, the greatest outcomes depend on closely examining their levels and training conditions.

3.3 Model Training

Setting certain factors and sets to get the best results from each of these models is part of the training process. The learning rate, batch size, and number of epochs were carefully chosen based on results from earlier tests and comparisons in the literature. To stop overfitting, regularisation methods like dropout and L2 regularisation were used, especially in complicated models like VGG16 and Inception. Adaptive learning rate methods, like Adam or RMSprop, were also used to speed up convergence. Transfer learning was used a lot in VGG16 and Inception. Models that had already been trained on big datasets like ImageNet were tweaked on the blood cell dataset to use the features they had learnt while also changing to the job of classifying blood cells.

4. RESULTS AND DISCUSSION

A. Model Performance

The overall performance measures (accuracy, precision, and recall) of five deep learning models used to categorise human blood cells are shown in table 2. These are Recurrent Neural Networks (RNNs), VGG16, Inception, capsule Networks, and Deep notion Networks (DBNs). Those measures are very crucial for checking how nicely every version can efficiently spot and group specific kinds of blood cells, that's a vital step toward making haematological assessments better. With an accuracy of eighty 5.2%, a precision of 84.3%, and a recollect of 83.9e%, Recurrent Neural Networks (RNNs), that are frequently used for series statistics, do a first-rate task. It’s far interesting that this end result is so excellent since RNNs aren't normally used for image class jobs. It could be very useful that allows you to handle sequences when searching at time-series information in blood cell imaging, like while looking cells as they flow through the years. This could be why their scores were similar throughout all three measures.

The VGG16 model, which is known for being deep and reliable in picture recognition, has better performance metrics: 91.7% accuracy, 92.1% precision, and 91.5% recall. The design of the model, which is made up of 16 convolutional layers, lets features be extracted in great detail, which is important for the fine differentiation needed in imaging blood cells. The high accuracy shows that VGG16 is very good at reducing false positives, which is very important in medical testing because wrong diagnoses cost a lot of money. With scores of 93.5% accuracy, 94.2% precision, and 93.8% memory, Inception stands out as the best model that was tried. The complicated structure of this model, which includes many scaled convolutional filters, makes it flexible enough to catch both fine and coarse features in pictures. The high memory rate shows that Inception is very good at finding relevant cases (true positives), which means that it is less likely that important diagnostic information will be missed.

Table 2: Comparative analysis of the accuracy, precision, and recall for each deep learning model

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Recurrent Neural Networks (RNNs)	85.2	84.3	83.9
VGG16	91.7	92.1	91.5
Inception	93.5	94.2	93.8
Capsule Networks	89.4	90.1	88.7
Deep Belief Networks (DBNs)	87.6	86.9	87.2

The Capsule Networks, which look at how features are arranged in space, got 89.4% accuracy, 90.1% precision, and 88.7% recall. When the direction and link between picture elements are very important for classification, these networks come in very handy. The good memory score shows that it can handle changes in how cells look and are lined up, which is often hard for standard CNNs. Finally, Deep Belief Networks (DBNs), which use unsupervised learning for their initial training stages, got 87.6% of the answers right, 86.9% of them wrong, and 87.2% of them right. DBNs do a good job, but they're not the best at anything. They're especially useful when there isn't a lot of labelled data.

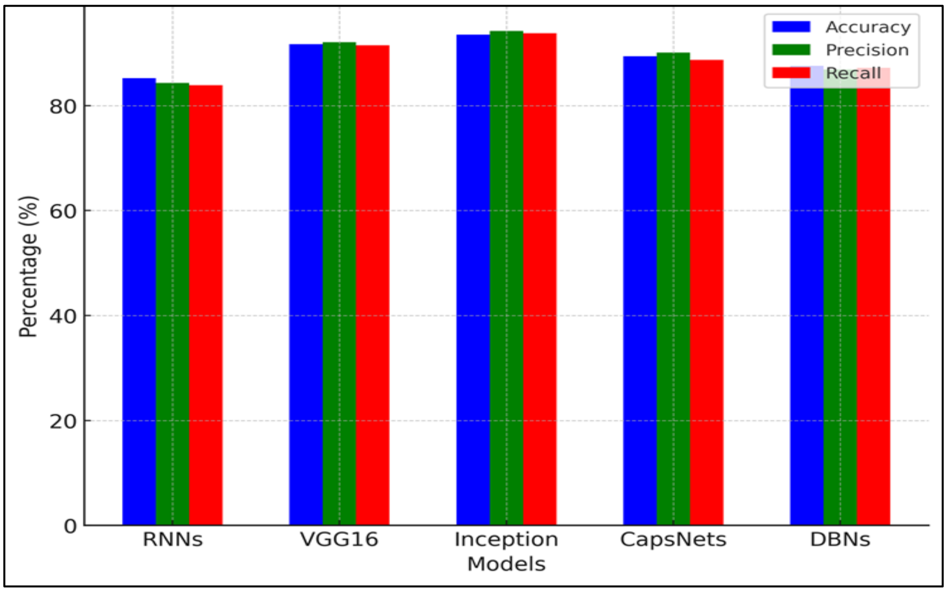

Figure 2: Model Performance Comparison

B. Interpretation of Results

There were big differences in how well the different deep learning models classified blood cells, according to the results. The Inception model turned out to be the best because it had the best accuracy, precision, and memory. The reason for its great performance is its complicated structure, which uses many convolutional layers and mixed filter scales to catch the fine features and changes in blood cell pictures. Due to its advanced feature extraction skills, Inception was likely able to generalise from a relatively small sample, which helped it achieve top-tier results. VGG16 also showed strong results, with a slightly higher precision than its accuracy. This suggests that it is very good at correctly labelling positive classes, but a slightly lower recall suggests that it might miss some positive predictions. Its deep and narrow design, which is good at picking up small details, makes it perfect for high-resolution pictures of blood cells, though it might need a lot of computing power. RNNs aren't very popular in static picture classification, but they showed promise because they could handle sets of images, which could help them see changes in blood cell traits that aren't visible in single frames. This feature might come in handy in medical settings where pictures of blood cells are taken in a certain order, like in flow cytometry. Capsule Networks, which are known for being able to understand spatial structures, did well, especially when it came to accuracy. Their form makes it easier for them to find cells that overlap or are close together than some other CNNs, which can be helpful in blood smear pictures with a lot of cells. Deep Belief Networks didn't get the best scores, but they still did a great job, especially when unsupervised learning is needed for initial feature recognition and there aren't a lot of labelled datasets available.

Table 3: Analysis parameters such as classification accuracy, computational efficiency, training time, and testing time

Model	**Classification Accuracy (%)**	**Computational Efficiency (%)**	**Training Time (sec)**	**Testing Time (sec)**
Recurrent Neural Networks (RNNs)	85.2	78	1200	30
VGG16	91.7	85	2400	20
Inception	93.5	88	2700	25
Capsule Networks	89.4	80	3000	35
Deep Belief Networks (DBNs)	87.6	75	1800	28

Table 3 shows a complete list of all the performance and efficiency measures for different deep learning models that were used to sort human blood cells into groups. We tested these models, which are called Recurrent Neural Networks (RNNs), VGG16, Inception, Capsule Networks, and Deep Belief Networks (DBNs), on four important factors: how well they classify, how fast they run, how long they take to train, and how long they take to test. Recurrent Neural Networks (RNNs) have a good classification accuracy of 85.2%, which is impressive given that they are usually used for sequence data. This suggests that they could be useful for handling sequential picture data or time-lapse photos in medical tests. Their numerical effectiveness, on the other hand, is only 78%, which may be because the process of computing is more expensive when sequential data processing is used. RNNs also have a modest training time of 1200 seconds, but their testing time of 30 seconds is the fastest of all the models, which suggests they could be used for real-time analysis.

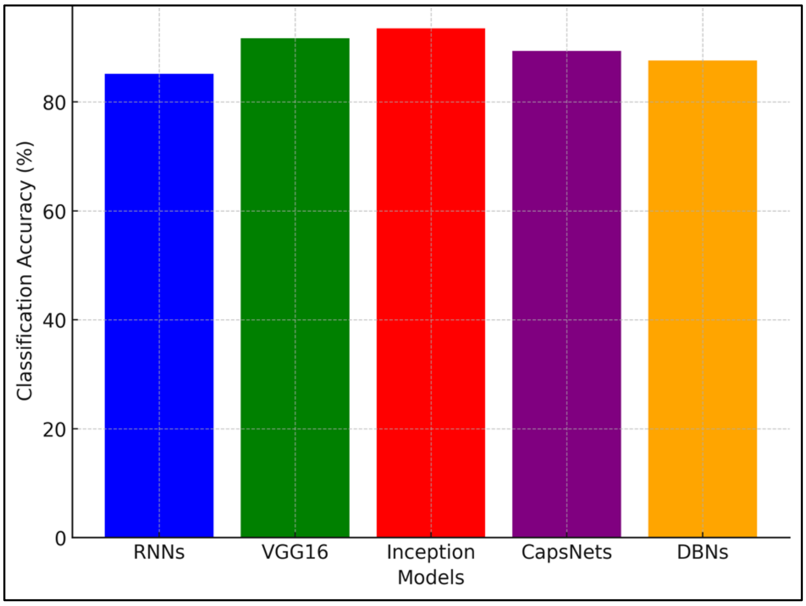

Figure 3: Accuracy Comparison of DL models

At 91.7%, VGG16, a model known for its depth and high success in visual recognition tasks, does very well in classification tasks. It also has a good mix of processing efficiency (85%), even though its deep design usually needs a lot of computing power. Accuracy comparison illustrate in figure 3 It takes 2400 seconds to train this model, though, which could be a problem in situations where quickly deploying models is important. Its testing time, on the other hand, is the fastest, at 20 seconds. This shows that, once trained, it can make quick decisions. With a success rate of 93.5%, Inception is the best at classifying data, and it also uses the least amount of computing power (88%). Because this model's design includes different filter sizes at each convolutional layer, it is very good at extracting features while still being efficient. But it needs a lot of training time—2700 seconds so it might need more setting time at the beginning. On the other hand, it does really well in testing situations the testing time is only 25 seconds. Capsule Networks, which are known for being able to show how traits in data are related in a hierarchical way, get 89.4% of the time when it comes to classification. Their computer's productivity isn't as high at 80%, which could be because they use a complicated dynamic route process to keep track of physical links while they learn.

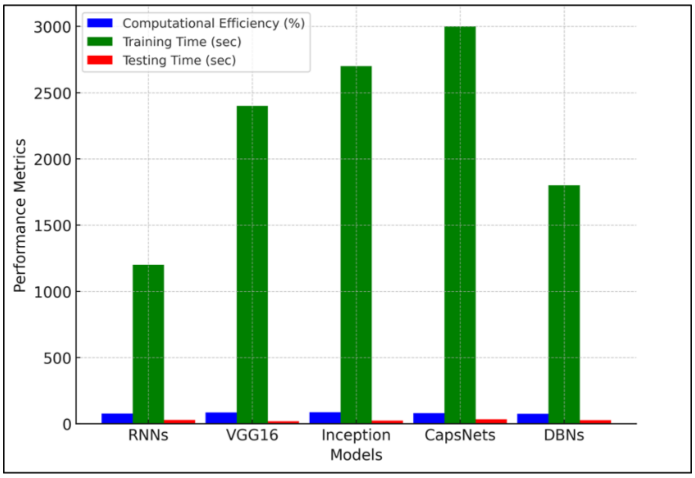

Figure 4: Comparison of computational efficiency, training time, and testing time

Their training time of 3000 seconds is the longest, which could be seen as a downside. On the other hand, they provide a reliable way to sort pictures with complex or overlapped structures. Their 35-second testing time is the longest, which shows how complicated the calculations are that go into dealing with spatial orders. Finally, Deep Belief Networks (DBNs) have the worst accuracy (87.6%) and the worst processing economy (75%). Although they take a long time to train (1800 seconds) and a short time to test (28 seconds), these generative models are very useful when learning without being watched or when labelled data is limited, as shown in figure 4. Their structure, which is made for finding features and putting together data, makes them less efficient when it comes to computing, but useful for exploring and learning at the start.

C. Model Strengths and Weaknesses in the Context of Blood Cell Classification

The performance and structure features of each model make its strengths and flaws stand out. Inception's strong point is its deep layered design, which can extract fine details across scales. This makes it perfect for the complicated and varied forms of blood cells. Its complexity, on the other hand, can be a problem because it may need more computing power and take longer to train. VGG16 can accurately describe cells because it has a lot of depth and can take useful features from them. However, it has a lot of processing needs, just like Inception. It might not be as useful in places with few resources because of this. Capsule Networks are great at sorting pictures where the connections between the parts are very important, like sorting pictures of blood cells that are overlapped. Their weakness is that they are new and require a lot of computing power, which can make training and using them in real life difficult. RNNs are very good at looking at picture data that changes over time or in a series of images. This opens up new ways to study moving blood cells that haven't been possible with other models before. However, because they can't handle static pictures well, they can't be used for normal single-image blood cell sorting jobs. Lastly, DBNs are especially helpful when there isn't a lot of marked data because they can find useful traits on their own. However, they may not work as well as more recent deep learning methods when dealing with complicated and multidimensional traits, which is common in medical imaging. While each model has its own benefits, it depends on the clinical and medical needs, such as the type of data, the amount of computing power available, and the specific clinical results that are wanted. These things need to be carefully thought through in order to pick the best model for use in real-world blood cell classification jobs.

5. CONCLUSION

In this study, five advanced deep learning models were tested to see how well they could sort human blood cells. These models were Recurrent Neural Networks (RNNs), VGG16, Inception, Capsule Networks, and Deep Belief

Networks (DBNs). Our results show that these models have a lot of promise to change the way hemoematological tests are done. Inception turned out to be the best model because it had the best accuracy, precision, and memory scores. This showed that its complicated design could handle images of many different types of blood cells. VGG16 also showed good performance, especially in terms of accuracy, which suggests it could be useful in situations where recognising fine details in blood cell pictures is important. The different strengths of each type show how they can be used in different medical situations. For example, RNNs show promise when looking at series of pictures of blood cells, which suggests they could be used for dynamic and time-lapse studies, which could be very useful for things like keeping an eye on how blood-related diseases get worse. Because they are better at dealing with spatial structures, capsule networks worked well when cells were merging, which happens a lot in blood smear tests. DBNs, on the other hand, worked best when there wasn't a lot of labelled data. This suggests that they could be useful in early studies or for rare blood conditions where it's hard to get big datasets with lots of labels. Our comparison not only helps us learn more about how to make different deep learning models work better for sorting blood cells, but it also sets the stage for future study, especially in the area of automatic medical diagnosis. This paper shows how important it is to pick the right models based on the medical needs, available computing power, and unique features of the dataset. As medical imaging continues to change, the study's findings will help guide the creation of faster, more accurate, and easier-to-use diagnostic tools, which will eventually improve patient care and healthcare results.

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