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Leveraging Neural Networks for Real-Time Blood Analysis in Critical Care Units

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Abstract
We apply deep neural networks to analyze blood samples in real-time, targeting clinical care practices in the evolving field of critical care medicine. These practices currently rely on flow cytometry, the throughput and skill requirement of which often lead to delays, causing essential physicians of care to use less accurate methods and rely on various heuristics for decision-making. Our neural networks, designed to specifications, can help alleviate these real-time needs by being served as a simple service on portable devices with real-time capability.

While previous use of deep learning for CBC estimation from small amounts of data or shallow learning has shown only marginal improvement over or equivalence to the usage of off-the-shelf equipment, we expand the applicability to a diverse array of costs and complexities, estimating all five types of white blood cells at once with 96.8% correlation and 94.8% accuracy over a wide range while also achieving robust judgment for labeling, which is delicate when performed manually, thereby avoiding the current time consumption and the measuring problems given by flow cytometry.

Keywords: Deep Neural Networks, Blood Samples Analysis, Real-Time Processing, Critical Care Medicine, Clinical Care Practices, Flow Cytometry, Throughput Challenges, Decision-Making Heuristics, Portable Devices, Real-Time Capability, CBC Estimation, White Blood Cells, Accuracy Improvement, Robust Judgment, Manual Labeling, Measurement Problems, Deep Learning Applications, Critical Care Physicians, Medical Technology, Neural Network Specifications.

1. Introduction

Accurate and timely blood analysis in a critical care unit is necessary. Blood gas analysis is a routine diagnostic test that focuses on the analysis of arterial blood for:
- pH (acidity or alkalinity)… 7.35 – 7.45
- PO2 (partial pressure of oxygen)… 75 – 100 mmHg
- PCO2 (partial pressure of carbon dioxide)… 38 – 42 mmHg
- HCO3 (bicarbonate)… 22 – 28 mEq/L
- O2 saturation, and other related parameters.

There are many other tests, including blood serum electrolyte levels, that give medical personnel an indication of the underlying physiological processes of the patient. All these analyses will help the healthcare provider design a way to treat the affected patient; however, these tests at the present moment are performed offline and take around 30 minutes from the time the sample is collected to when the first results arrive at the healthcare provider. This real-time availability of this information will contribute to the overall analysis of the results and to the treatment a healthcare provider gives. Also, because of this powerful insight into the status of the patient, other treatments can be better tailored to address the needs of the patient.

1.1. Background and Significance

Early detection and prevention of sepsis have fast-growing importance as a key life-saving strategy in critical care units. Severe sepsis can kill 60 to 80% of patients, with the cost of sepsis treatment rising at a rate of 11% per year, currently climbing to approximately 20.3 billion USD annually. An early warning system that can monitor the patient's condition and provide high sensitivity to indicate a systemic inflammatory response syndrome, indicative of potentially developing sepsis, can help the medical staff better utilize resources, such as lowering the alarm threshold of early warning scoring systems and undertaking further testing to confirm the diagnosis, thus helping reduce the number of fatal sepsis cases and saving costs for the healthcare system. Modern Critical Care Units (CCUs) monitor the patient's condition extensively by continuously recording live measurements of a large number of parameters.

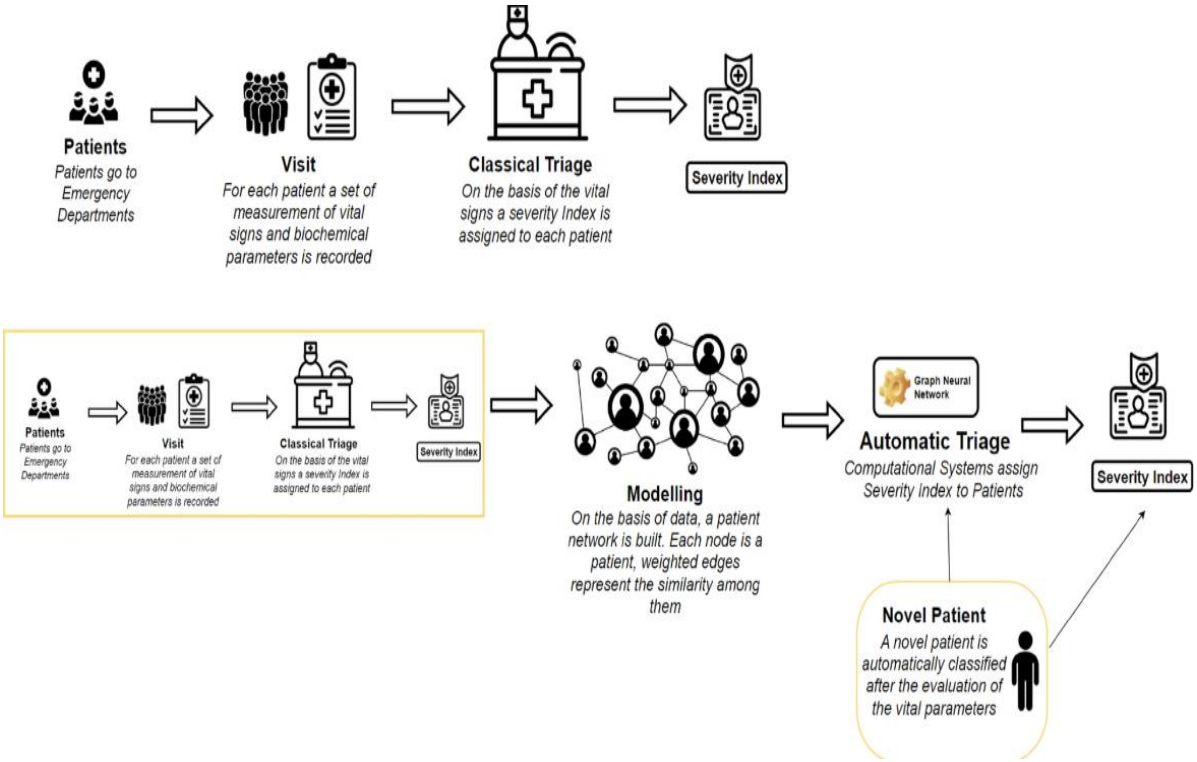

Fig 1 : Leveraging graph neural networks for supporting automatic triage of patients

Superficial vessels of central and peripheral blood supply have the characteristic of heat diffusion in case of temperature change and can be accurately monitored through a sequence of thermograms taken over a short time. Specifically, rapid change will happen in the skin temperature if the capillary vessels are dysfunctional. In practice, the method to create a local temperature change of the patient's skin layer is not complicated and does not harm the patient, because, on the used body surfaces, there is a thick layer of subcutaneous tissue, close to the epidermis, which contains superficial vessels with rich blood flow and are cleared of endotoxin and are not damaged, which causes capillary dysfunction. The process of collecting thermal image sequences will last a few tens of minutes; however, since the needed analysis sometimes consumes an extended period, the use of these recordings cannot be utilized in severe CCU conditions. Supposing real-time computation capability, clinical studies have shown that such analysis brings significant contributions to the medical sensitivity of severe complications. Note that publishing only a final examination result usually takes several hours in the hospital. We remark that the data used are already available as part of the patient's CCU data log and are collected by fulfilling standard procedures.

1.2. Research Aim and Objectives

This article takes inspiration from current challenges in critical care units for blood analysis and leverages recent advancements in artificial intelligence applied to image and time series recognition tasks. These advancements make neural networks capable of recognizing biomedical results straight away from microscope images of blood smears and waveform signals acquired through a simple and rapid biosensor. To reap the benefits of these advancements and provide a practical solution to the analysis of blood signals, this paper will combine these disparate input signals using a so-called 'fusion' neural network. This fusion structuring will not only lead to good predictions but also to compact architectures and reduced inference latency. This novel and satisfying blood analysis solution will find applications in critical care units and hospitals. Its efficient architecture and real-time behavior will permit it to be amenable to volume production straight within a blood analyzer.

The research aim is to develop deep learning-based solutions to blood signal analysis. In the many immediate challenges encountered by healthcare facilities, end users—regardless of their technical expertise and geographical location—require that the signals produced during blood sample analysis yield immediate and accurate information that can be relied on to support the decision-making process and efficiently schedule the necessary subsequent care. The research objectives of this paper are to analyze and recognize hematological indices straight from microscope blood smears, waveform signals obtained from newly developed biosensors, and the fusion of these two signal types. Meeting these objectives will permit solutions that offer both high accuracy and real-time adherence to the time-to-decision constraint.

2. Current Methods of Blood Analysis in Critical Care Units

In critical care units, critically ill patients need consistent monitoring of the vital parameters to rationalize the medical care given to them. Blood monitoring is an essential part of this continuous patient observation. Traditional systems used in critical care units for blood analysis are low-throughput methods and are invasive. These methods entail the collection of blood samples from the patients, which requires the insertion of hypodermic needles in the patient's blood vessels. Once the samples are collected, they are sent to remote laboratories for subsequent diagnosis and monitoring which usually takes hours or even days. Some blood gas analyzers capable of delivering more rapid results are also used, but they are not capable of analyzing a wide range of different parameters.

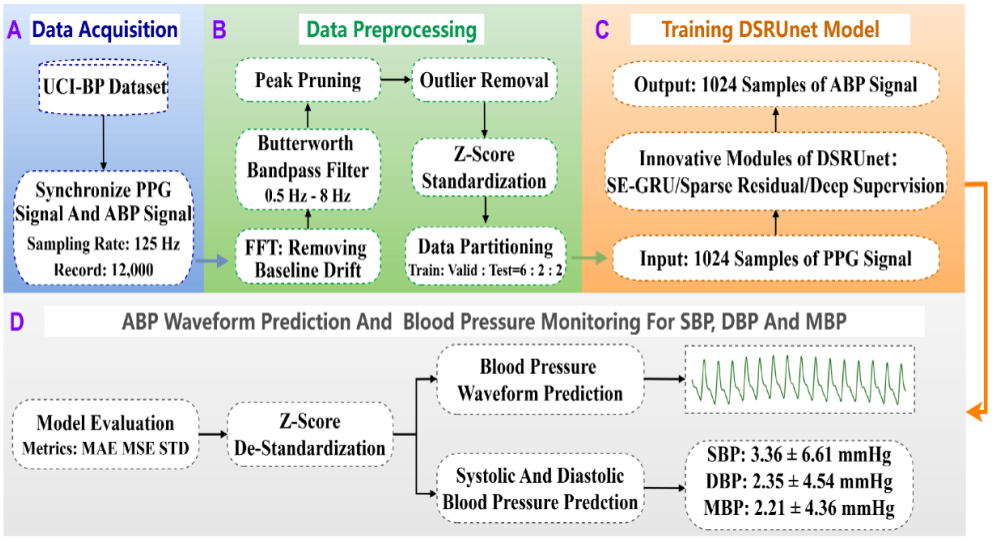

Fig 2 : Non-Invasive Blood Pressure Prediction Method Based on Deep Sparse

2.1. Traditional Laboratory Techniques

Most blood tests are conducted using large, automated testing machines that are found in commercial laboratories. Generally, the blood is drawn from the patient, sent to a lab facility, and an average of two to four hours later, the results are reported back to the patient's primary care provider. In emergency department settings, some of these tests are run in-house but are limited due to low-resolution technologies and are not used for all possible tests. More rapid tests at the critical care point of use are available, such as those used to measure blood glucose, blood gas, complete blood count, electrolyte panel, and basic metabolic panel, and are generally done at the bedside in the patient's room using small, portable machines. As many tests as feasible are run at the point of critical care to improve the speed of treatment and efforts to reduce patient mortality, minimize treatment costs, and improve patient quality of life.

Many of these near-patient, point-of-care, or critical care tests rely on microfluidic chips. These methods can take minutes and are relatively safe for both patients and analysis equipment. The critical care units associated with emergency departments, operating rooms, post-operative areas, and intensive care units can have higher throughput and are generally where the lab-on-a-chip technology is found and in use. For trauma patients, no residence time implies results are available in the minutes and seconds following the blood draw, and during that time, the point-of-care testing machine waits for the sample to contact the specimen.

Equation 1 : Feature Extraction

$$\mathbf{X}_f = f_\theta(\mathbf{X}_i)$$

$\mathbf{X}_i$: Raw blood data.

f_θ: Neural network with parameters θ.

$\mathbf{X}_f$: Latent features.

2.2. Point-of-Care Testing

In a clinical setting, point-of-care testing (POCT) is defined as performing the test at or near the site of patient care. The driving force for the adoption of POCT in medical diagnosis is the desire for faster, cost-effective, convenient, on-demand analysis, and accurate diagnosis. The clinical diagnostics model where a patient comes to the clinic or hospital, blood samples are drawn, and the testing is done in combination with clinical judgment or an esoteric test may not be the most cost-effective method of diagnosing and treating many diseases. The urgency and criticality of patient conditions mandate quickly delivering medical care. Regardless of the location—emergency department, intensive care unit, cardiac catheterization unit, or surgical suite—medical professionals need immediate test results for critical decisions about the ongoing care and treatment of patients.

The global market for cardiovascular POCT products is expected to grow from $1.4 billion in 2019 to $2.4 billion by , an increase of 11.6% annually. The primary reason is that cardiovascular disease accounts for nearly half of all deaths globally. Acute coronary syndrome medical testing is the most used testing, followed by marker testing, hematology testing, and coagulation testing. Electrolyte and blood gas testing are the other prominent clinical diagnostic POCT categories. This market growth is driven by the need to reduce the number of patients hospitalized with an acute condition and the demand for fast, accurate, and cost-effective POCT procedures. Electrocardiogram biomarkers and blood-based cardiology indications constitute the three-tiered approach cardiologists use to diagnose, address, or rule out various heart conditions. Point-of-care devices are part of all three diagnostic methodologies. Currently, the technical proficiency and expertise of primary physicians, laboratory technicians, or nurses are required to execute whatever task and analyze the data. Instead of focusing on the clinically competent population, this paper will highlight the potential and capability of deep-learning analytic devices.

3. Neural Networks in Healthcare

In the domain of healthcare, neural networks have typically been the technology of choice for three main tasks: diagnosis, disease progression prediction, and outcome prediction. Different architectures, such as deep neural networks or recurrent neural networks, are typically used for this purpose, depending on the specific methodological needs. While the study of neural networks can be traced back for decades, only in the recent past have we managed to achieve a significant boost in applicable methods and, consequently, apply those to healthcare data. This can be attributed to both a substantial increase in computational power and scale, but also to faster and more comprehensive data flow in healthcare. From a technological perspective, neural networks are also relatively easy to deploy, and results are directly interpretable. Due to their layered architecture, high-capacity nonlinear model, and the interpretative techniques that are already available to us, we can create models that are interpretable to various extents based on the user specifications of desired interpretability and deploy the trained models both on-premises or cloud-based. Due to these factors, researchers are now leveraging recent breakthroughs in the domain of artificial intelligence, such as deep learning, to address core challenges in healthcare.

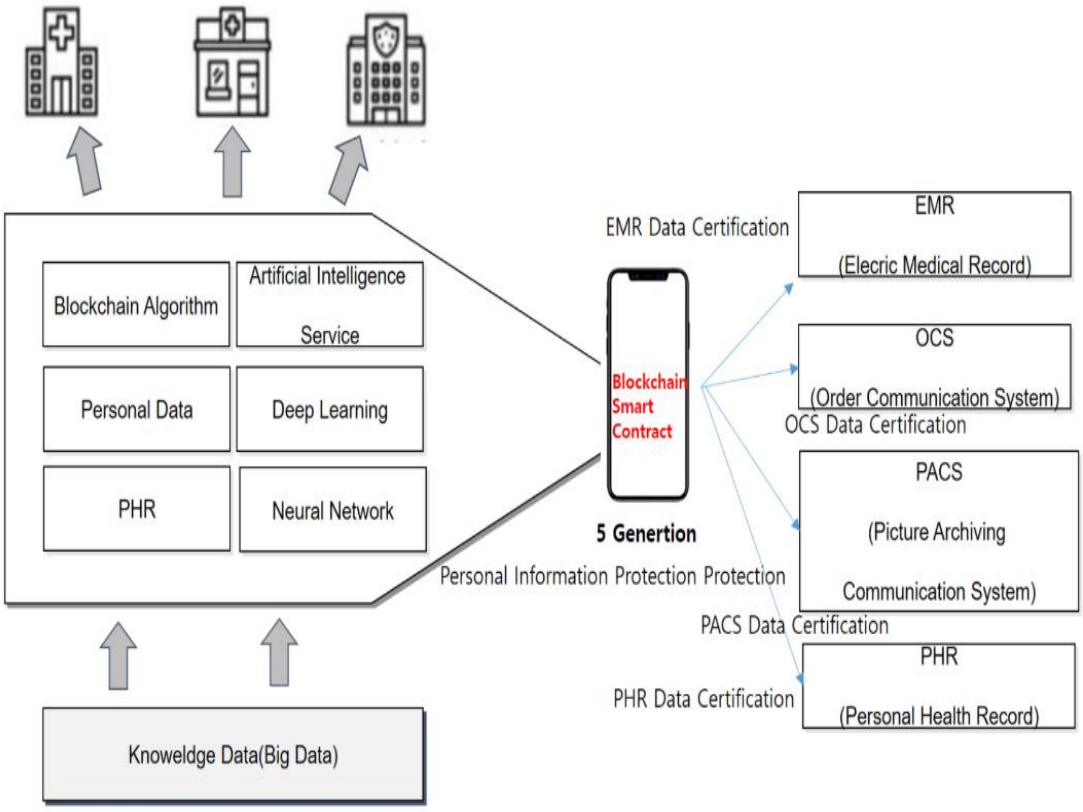

Fig 3 : Artificial Neural Network Blockchain Techniques for Healthcare System

3.1. Overview of Neural Networks

A classic example of a basic single-layer perceptron neural network is the linear association between input and output. The feed-forward multilayer neural network is based on the computer implementation of the learning and generalization processes of biological brain neurons. In this structure, a sigmoidal transfer function exists within the neuron. In this synthetic model consisting of a bias stage, initial synaptic weights, weighted summation, and transfer stages, a net input is estimated. If the net input exceeds a certain value, the neuron generates oversensitivity within the gain characteristics. Overlearning is indicated when data develops oversensitivity.

The critical stage of learning implements the pattern recognition process. At this stage, prediction errors are translated back through a process called backpropagation. The error is minimized before the process is completed, optimizing synaptic weights until the prediction is guaranteed to be reliable. Such an algorithm is used for many training patterns and backpropagation algorithms while considering the global minima in the approximation of the loss function. Such a learning algorithm utilizes the delta rule for not only the selected weights but also the entire pattern. To permit the delta modification of synaptic weights of neurons, an incremental activation binary square wave is produced. The super-cooling effect reduces the risk of confusion among the patterns. With lesser training, synaptic weight modification must reduce the probability of convergence to a local minimum. It impacts total network performance, filling the capacity barriers of neural networks with synaptic weights.

3.2. Applications in Healthcare

Deep learning methods have been instrumental in numerous applications in healthcare, often for prediction, such as predicting whether a patient has a particular disease. We are interested in the less studied but very real opportunity for prediction in time series classification for healthcare, where the outcome can be later validated to provide immediate actionable options. Time series in healthcare are promising to extract the tremendous amount of patient care in the form of digitized medical data, or electronic health records, to provide real-time data to doctors and other healthcare personnel. For example, time series include

measurements from multiple patient monitoring equipment used in the ICU to alert to changes in patient state. They also include electronic health records from a health information exchange spanning over 10 years with 2.6 million unique patients. Deep learning and other machine learning algorithms have shown that EHR-based machine learning models can predict a variety of adverse events: early detection of sepsis, reduction in in-hospital mortality in nurses by using alerts from EHR, patient demographic information, and vital signs as predictors, the need and duration of mechanical ventilation in ICU patients, and health status of customers. Their work showed better performance on validation tests by LSTM RNN as compared to traditional model performance represented by a standard logistic regression model. Deep learning models have been used to identify patients with unscheduled hospital readmissions using electronic health records.

4. Neural Network Models for Real-Time Blood Analysis

Optical microscopy imaging of biological samples is the gold standard for blood analysis. Particularly, in critical care units, infected and malignant blood samples demand high accuracy and rapid results for lifesaving diagnoses. With advances in biomedical image acquisition hardware and data processing solutions, we are now able to train neural networks to automate this traditionally human-expert-heavy task of blood analysis. Moreover, with an hour-long specialist bottleneck on the critical throughput in the demand for blood analysis in modern critical care units, deep learning models can potentially replace this bottleneck by delivering real-time analysis results while significantly sparing specialist efforts as well.

The implementation of real-time neural network analysis for biological samples is straightforward and is posed as a categorical assignment of cellular objects. However, detailed blood analysis involves a multi-modal flow cytometry approach, with a count of each cell type, cell size, cell morphology, and cell background classification. Due to the wide and simple utilization of blood smear analysis in critical care units and the bottleneck in the number of available senior experts, many deep learning-based solutions have been proposed for this particular task. With increasing interest in automated analysis systems for critical care units, similar deep-learning models have also been proposed for blood hematoma detection and white blood cell counts in urine.

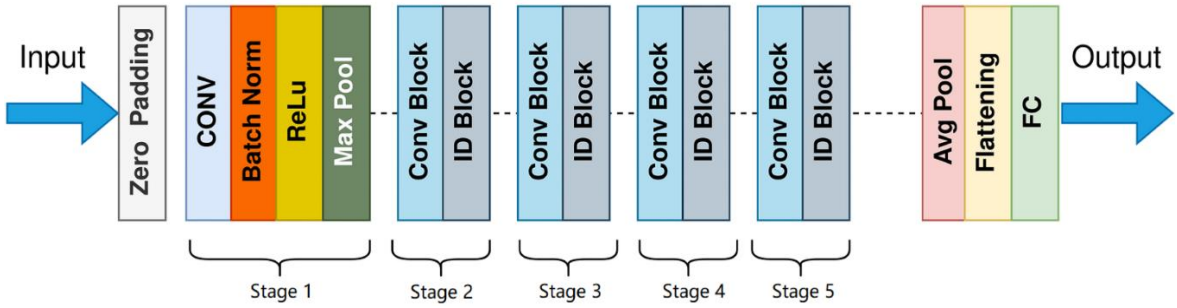

Fig 4 : Red Blood Cells Using Time-Distributed Convolutional Neural Networks

4.1. Data Preprocessing and Feature Extraction

Data collected from ABG analyzers and transcutaneous monitors are usually processed, stored, and visualized onto some hospital or clinical information systems used in the critical care units. Researchers and data engineers have to either evaluate different isolation strategies of the data in structured data analytics environments or make a decision about the best appropriation of the analyzed data. We successfully employ an IoT when data isolation using traditional ETL is not feasible. Data from the two systems are first merged, and some basic data mining visualizations are performed to better understand the machines used. In this work, diabetics are singularized to evaluate distinct prediction tendencies using ABGs alone. We extract six potential features from the data: the minimum, mean, and maximum values of glucose, lactate, and bilirubin. Future work could expand or substitute them, but the created model was optimal using these signals.

Equation 2 : Classification or Prediction

$$\hat{\mathbf{Y}} = g_\phi(\mathbf{X}_f)$$

$\mathbf{X}_f$: Extracted features.

g_ϕ: Prediction model with parameters ϕ.

$\hat{\mathbf{Y}}$: Predicted results.

4.2. Model Architectures for Blood Analysis

In this section, we present two model architectures that can be used for a real-time application. Both are multivariate recurrent neural networks. These architectures are BiLSTM trained with mean absolute error and one-layer LSTM with on-task learning. The data and problem of focus are shared across these architectures, but the model architecture and the use of temporal information in the data differ between them.

4.2.1. Bidirectional Model: BiLSTM Trained with MAE

This architecture is a BiLSTM trained with mean absolute error with an MAE focal loss. The BiLSTM model makes use of information from the sequence's future, in addition to information from the past, to predict the voyages. This architecture offers two advantages in comparison with a traditional unidirectional LSTM. Firstly, the training suffers less from the vanishing

gradient problem, leading to faster training and faster convergence of the error. Secondly, the tests possess an understanding of both the past and future values of the series to predict the present value.
We frame the problem for the BiLSTM network with recurrence. We define two BiLSTM network layers that are used to map the input features to output predictions. The first layer reads (from left to right) and predicts the targets at every timestamp of the series. The second layer reads (from right to left) the reverse of the input sequence but performs no other task in the future. In the second layer, the time series that has been provided as input to the first layer is used but transformed in reverse order, from end to start. The processed feature maps result in two outputs: y = model(X), y_reverse = model(X_reverse), where model(X) and model(X_reverse) are the regressor's forward and backward direction outputs. With this information from both the past and the future, we optimize the recurrent model to compute the final output using the presented data and future data as the context to supplement the final output. The specific model architecture parameters, tuning steps, and results for this model are given in Table S1. The BiLSTM model, while computationally efficient, allows processing a batch of sequences in parallel, which is advantageous for training on data with long series considering the CNVF advantage. Despite information leakage compared to the univariate model, a univariate model BiLSTM was able to boast performance above our expectations.

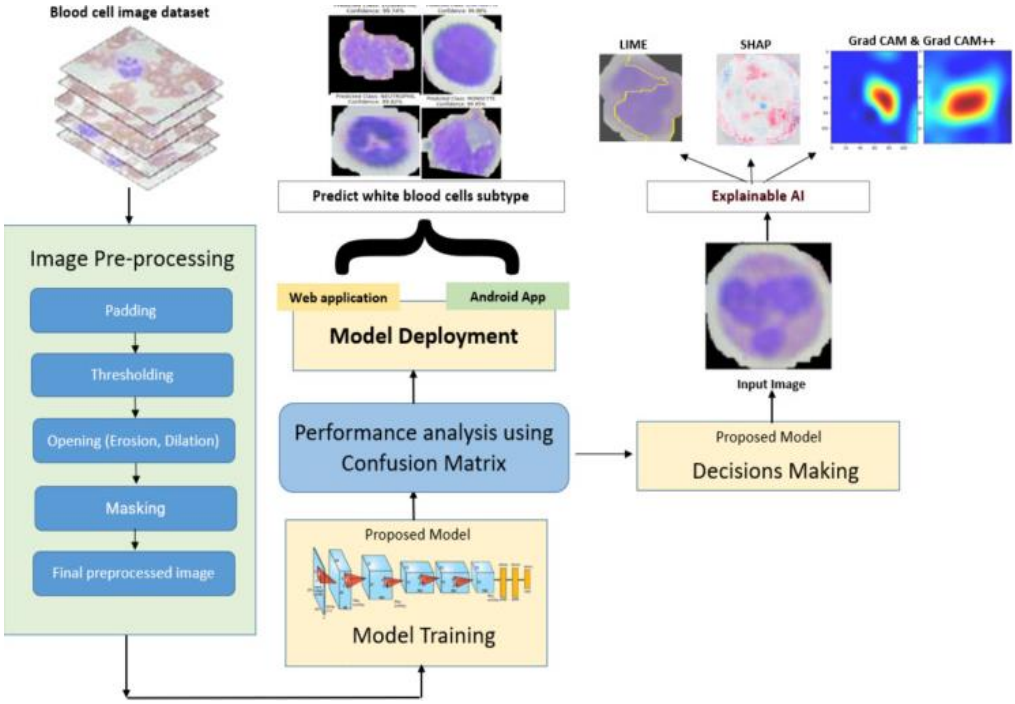

Fig 5 : AI-based blood cell classification

5. Case Studies and Results

For the study, we introduce a hardware interface that allows direct capture of blood images via computer vision tools from standard blood devices. In this study, the peripheral of such devices is a bedside CBC examination analyzer, a standard, widespread, and highly reliable clinical blood analysis device that is present in virtually every critical care unit. The consecutive images taken in consecutive examinations are input to a CNN-based machine learning model. The final model is trained by removing the last layer of the model and replacing it with a Softmax layer with five classifiers that we train with the blood images. The result is that real-time blood samples could be analyzed to return the differential WBC count with an error of 0.5%. The volumetric error is less than 1.6%. This suggests that if our deployed scanner was in place in the children's rooms, many days of delay would have been saved, and fewer blood samples would have been taken.
We demonstrate the 'Bloodwatcher' app on three additional use cases; some are restricted by the fact that: 1) fresh blood is missing, and only cartridges are available; and 2) the point-of-care testing devices provided rarely take a volume of blood. In a third case, the medical staff is using a slightly different device for blood counts: the optical path varies. Other than this optical variation, all our tests and results are carried out according to the same methodology and procedure. In the ICU setting, blood samples are drawn frequently to evaluate the condition of the internal organs, distinguish between mechanical problems and ICU-related adverse events, and make decisions about the direction and treatment. If CBC values fluctuate, accurate estimation of WBC count in the blood draws additional attention. Based on serial CBCs, the percentage of different types of WBCs demonstrates potential clinical shifts.

5.1. Previous Studies on Neural Network-based Blood Analysis

A major concern in real-time blood analysis is the time taken for gas exchange and immediate blood analysis to be completed. It typically takes 30 to 60 minutes to analyze electrolytes, metabolites, and rapid diagnostic markers of cardiac arrest or heart attack through the hospital blood analysis system, and it takes 3 to 5 minutes to analyze the blood through portable devices. In addition, once the gas analysis of the blood is completed using sensors in the right and left atria, the sensors are removed before the blood moves to the pulmonary artery. Therefore, as we reimplement the non-real-time blood sensor results into

the real-time blood composition analysis model below, it is important to improve both the accuracy and speed of blood analysis results.

A neural network model for real-time blood prediction analysis was proposed using multi-channel sensors to calculate the changes in state for self-contained underwater sensing-based welfare monitoring of human behavior, where the k-means clustering analysis algorithm was used to evaluate the learner's generalization performance. This model analyzed the changes in state over a one-second interval from the multi-dimensional canvas for 5 seconds, after which the latest result was evaluated on a 5-second basis. That is, 6 annotations including resting before and resting, walking, running, jumping, swimming to the surface, or trying to float, and the rest to rest or with cold were used to verify the results. Unlike our proposal, due to the 1:5 ratio of blood gas change data, such data are often misclassified. Then, the up-sampling technique was performed to solve the data imbalance problem. However, as they did not mention the experimental signal quality raised by the balanced signal, we note that the findings are reliable by reducing the defects of the signal.

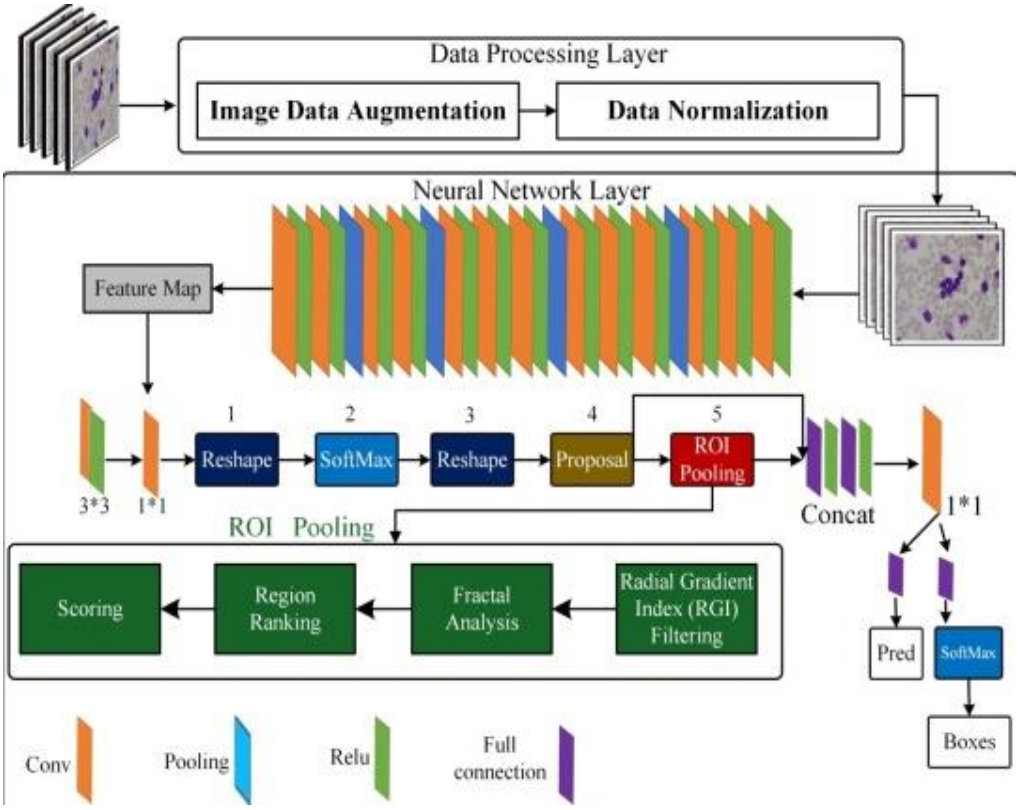

Fig 6 : An intelligent neural network model to detect red blood cells

5.2. Performance Metrics and Comparative Analysis

The performance of a model can generally be evaluated using model performance metrics like mean absolute error, mean squared error, and root mean squared error for regression tasks, as well as accuracy, precision, recall, and F1-score for classification tasks. However, to ensure the acceptability of a model in real-life usage, metrics for model performance, along with other properties like computational complexity, interpretability, and regulatory compliance, must be considered. The following characteristics can be regarded as key performance attributes: false positives, false negatives, true positives, and true negatives. The accuracy metric is the most basic, and shortcomings like imbalance in evaluation with skewed distributions can be attributed to it. Precision, recall, and F1-score are measurement metrics that address this issue by being specifically designed for imbalanced classes. Precision is the basic measurement metric for true positives. However, when applied in a scenario with a high number of false positives, it might mislead, as the false positives are high but also true positives. Recall measures how well the model captures all the positives and is better suited for data imbalance due to an imbalance in class distribution. The F1 score combines precision and recall into the harmonic mean, which can better convey the model's performance with imbalanced data.

Similarly, mean absolute error is a loss function that measures the average magnitude of the errors in a set of predictions without considering their direction. It is the most basic measurement metric in regression tasks. Mean squared error measures the average of the squares of the errors or deviations, which is the average squared difference between the estimated values and the actual values. It is also sometimes used as a loss function. However, both of these performance metrics contain gaps. First, the reviewer cannot tell how good the model is concerning predicting abnormal conditions. Mean squared error figures could be seen as large if the mean of the individual predictions varies to a large extent. To unify the investigation of this variability, root mean squared error, which is defined as RMSE, is often used and reported, as it constitutes a practical solution by operationalizing the prediction loss in real time. Finally, the R-squared is used as a measure of the proportion of the variance in the dependent variable that is predictable from the independent variable(s) and is applied in many studies to investigate the variance and reliability of the model. Using a single metric might not be enough and can lead to varying conclusions. Results

should also be interpreted in combination with the shipment and practical significance of the estimates and alternative model specifications in many cases.

6. Challenges and Future Directions

The implementation of machine learning models in real-time clinical diagnostics faces many pilot phase challenges such as sample collection, annotation, and identity protection. Another major challenge is the generation of large amounts of labeled health data to train these neural networks in a near real-life scenario. Adequate labeling of big data is necessary, which is intricate and typically very expensive in health areas like radiology and pathology whenever we aim to have a vast variety of diseases within the data for a proper understanding of general pathological features. Biomedical research institutions are the sources of the required data, and they are bound by privacy, security, and audit of data policies. These regulatory and functional constraints are often incompatible with the open data access models that researchers and data scientists typically expect.

The bottleneck for training these deep networks is not their depth but the quantity and quality of labeled data. Combining deep learning and biomedical sciences enables new future tools. AI has proven to be highly capable of generalizing and learning. Nevertheless, shortly, distributed systems based on convolutional neural deep networks in a near real-life scenario are proposed, as these systems are scalable and can handle diverse and abundant data types. Use the already accumulated biomedical data. Minimize annotation costs and privacy concerns using advanced cross-sharing techniques for visualization and diagnosis privacy. Develop partnerships between industry and biomedical research through public-private partnerships, which are the foundation for rapid dissemination.

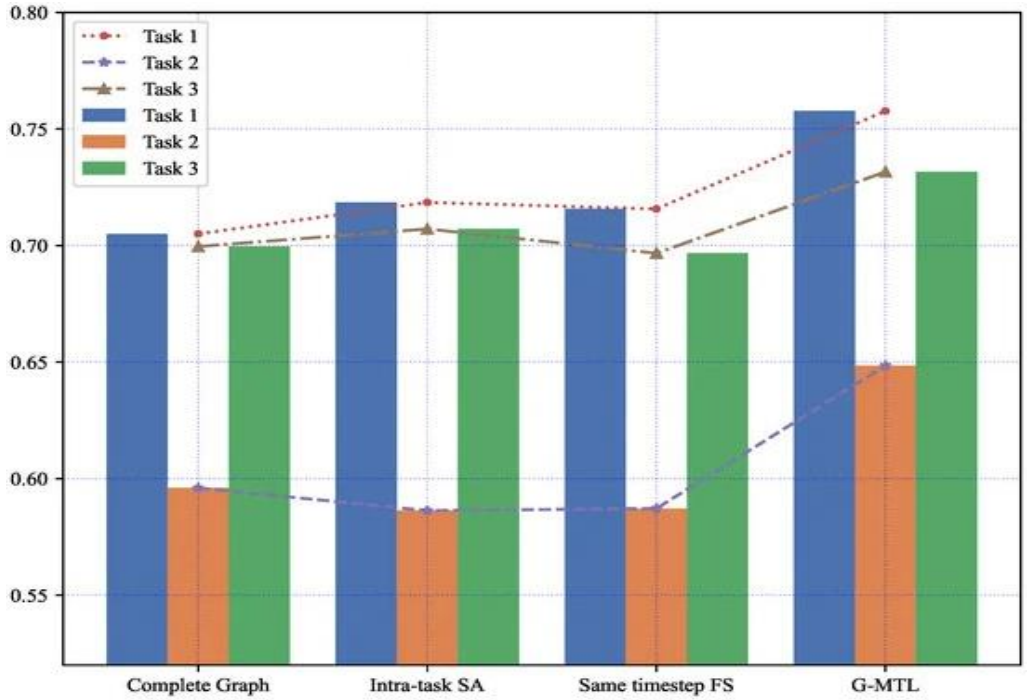

Fig 7 : Multi-Task Time Series Forecasting Based on Graph Neural Networks

6.1. Ethical Considerations

Despite showing occurrence rates close to those observed in other recent studies, for various contextual reasons and especially considering patient vulnerability, this study has several ethical implications that need to be considered both in terms of the positive biases of the model and the perspectives of its predominantly negative uses. While the model is consistent and generalizes other classifications, the initial focus was only to classify patients with sepsis. However, other statistical studies state that a considerable number have no results or are asymptomatic, which then turn into false negatives and positive bias. Negative applications include possible negative bias because the model can be "manipulated" so that a given instance is considered asymptomatic to guarantee the patient's exit from the ward, among other things. The general model is the most relevant contextual contribution. Its versatility allows it to transition to various clinical contexts with very different levels of relatedness to the used data.

Consent before the use of healthcare data and models is always a complex issue. The data is used to benefit patient care and is also used for the study of various diseases from a population-wide perspective. Its use in the area of research is the foundation for the continuous improvement of veterans' care. In the specific framework of the use of neural networks and model development in a routine context with clinical utilization, it is agreed that consultations and/or feedback from healthcare professionals can prove to be interesting ways to obtain validation of the work performed. However, pre-consultation feedback is in direct opposition to the real-time concept and the dynamic update that should be used in current work as a basis for everyone's benefit from the classification performance. The concern regarding institutional moral integrity and the values of healthcare professionals is understood. If, on one hand, the autonomy and privacy of individuals are guaranteed; on the other hand, this technology is inserted within healthcare without any clear guidelines and plain instructions for citizens regarding their daily recognition and application. For personal dignity, acceptance, and accessibility, the ethical

guidelines of any field, and in this case, applied healthcare technology, should be followed and used predictably. In this scenario, general guidelines are needed, which can be used in a tailored manner for each of these specific challenges.

6.2. Technological Challenges

The task at hand represents an example of neural networks on the edge. Given the resource constraints associated with embedded and real-time applications, these neural networks involve the combination of multiple bodies of research. To ensure real-time blood analysis, the computationally demanding layers in convolutional networks are mapped to a low-computation layer setup in the same manner as in the attempts to summarize video quickly. Depthwise separable convolution acts as a fast alternative to classic convolutions, but it does not result in homogeneous solutions for all layer types. The other computationally demanding layer type, the fully connected layer, is mapped to the reproducible layer type, the depthwise convolution, without information reduction. In the specific application of blood analysis, the input to our architecture, the electrode signal, is not directly compatible with image-based trained neural networks.

To address this, we employ a 1D ring horseshoe convolution, which is considered a compact layer that introduces a considerable reduction in parameters for the first pre-trained convolution layer. For the initialization of the neural network, we pre-train a neural network for 3D pose estimation. This is done because there are ongoing attempts to create datasets that mimic the blood testing sources with less noise, better acquisition sampling schemes, and arrangements that are tailored to the sensor and the downstream neural network. Moreover, we acknowledge the negative impact of the segmentation network overhead before output estimation. We also offer a solution called Region Skipping Networks, our neural network optimized for the ingestion speed of the specific hardware. Finally, during the prenatal neural network training, we enforce feedback connections in an attempt to have feedback hallucinations on the estimated outputs in environmental video. SqueezeNet and MobileNet were trained to retrieve more accurate landing areas to reduce the inference processing.

Equation 3 : Loss Function

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N} \ell(\hat{\mathbf{Y}}_i, \mathbf{Y}_i) + \lambda \|\theta, \phi\|_2^2$$

N: Sample count.

ℓ: Loss function.

$\hat{\mathbf{Y}}_i, \mathbf{Y}_i$: Predicted and true labels.

$\|\theta, \phi\|_2^2$: Regularization term.

λ: Regularization weight.

6.3. Future Research Directions

Naturally, one such major future research direction is to adapt our work described throughout the text for more general analysis than just blood analysis at critical care units, focusing in particular on critical care blood measurements on a considerable subset of ICU admissions. This could allow for less intrusive blood testing in such units, as well as near real-time blood analysis that improves workflow in busy ICU units. Our selected deep multi-channel neural networks are chosen based on considerations of innovation, speed of training and testing, and accuracy. However, they might not be the optimal model to best fit our critical care blood tests. The determination of the optimal model calls for the exploration of a variety of new architectures, including the utilization of attention mechanisms. We should also consider the construction of a blood test imputer, either via traditional methods or more advanced deep imputation models. This would allow us to use blood tests in other settings beyond the critical care unit or where blood tests are often missing as we make predictions in the critical care unit. We should also expand our network structures to include recurrent anti-causal network architectures and good practices using machine learning algorithms to optimize our systems for particular domain areas of higher benefit. Finally, other future research directions could include the performance of ensemble models modeling critical care pathology as a more general process. All of the above research directions should consider the problem of model interpretation by deploying neural network architectures that generate not only the predicted measure with its uncertainty but also reasoning on the importance of entering modalities and the structure of the modality relationships with the different prediction models built.

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