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A Hybrid CNN-RNN Model for Enhanced Anemia Diagnosis: A Comparative Study of Machine Learning and Deep Learning Techniques

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ABSTRACT

This study proposes a hybrid Convolutional Neural Network-Recurrent Neural Network (CNN-RNN) model for the accurate diagnosis of anemia types, leveraging the strengths of both architectures in capturing spatial and temporal patterns in Complete Blood Count (CBC) data. The research involves the development and evaluation of various models of single-architecture deep learning (DL) models, specifically Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Fully Convolutional Network (FCN). The models are trained and validated using stratified k-fold cross-validation to ensure robust performance. Key metrics such as test accuracy are utilized to provide a comprehensive assessment of each model's performance. The hybrid CNN-RNN model achieved the highest test accuracy of 90.27%, surpassing the CNN (89.88%), FCN (85.60%), MLP (79.77%), and RNN (73.54%) models. The hybrid model also demonstrated superior performance in cross-validation, with an accuracy of 87.31% ± 1.77%. Comparative analysis highlights the hybrid model's advantages over single-architecture DL models, particularly in handling imbalanced data and providing reliable classifications across all anemia types. The results underscore the potential of advanced DL architectures in medical diagnostics and suggest pathways for further refinements, such as incorporating attention mechanisms or additional feature engineering, to enhance model performance. This study contributes to the growing body of knowledge on AI-driven medical diagnostics and presents a viable tool for clinical decision support in anemia diagnosis.

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1. INTRODUCTION

Anemia is a prevalent health condition characterized by a deficiency in the number or quality of red blood cells (RBCs) or hemoglobin, leading to impaired oxygen transport to tissues [1]–[3]. This condition affects millions worldwide, with significant implications for morbidity and mortality, particularly in vulnerable populations such as children, pregnant women, and the elderly [4]–[6]. Accurate and timely diagnosis of anemia and its various types is crucial for effective treatment and management [7]–[9]. Traditional diagnostic methods often rely on manual interpretation of complete blood count (CBC) data, which can be time-consuming and prone to human error [10]. Recent advancements in Machine Learning (ML) and Deep Learning (DL) offer promising avenues for automating and enhancing the accuracy of anemia diagnosis [11]. The increasing availability of large-scale medical datasets and advancements in computational power have catalyzed the application of ML and DL techniques in medical diagnostics [12]. These technologies enable the analysis of complex, high-dimensional data, uncovering patterns and relationships that may not be apparent through traditional statistical methods. In this context, hybrid models that combine the strengths of different DL architectures have emerged as a powerful tool for improving diagnostic accuracy.

The urgency of this research lies in the global burden of anemia, which demands efficient and accurate diagnostic tools to facilitate timely intervention [13]. According to the World Health Organization (WHO), anemia affects approximately 1.62 billion people, constituting about 24.8% of the global population [14]. The condition is associated with adverse health outcomes, including cognitive and physical impairment, increased susceptibility to infections, and complications during pregnancy [15]. Therefore, developing robust diagnostic models that can accurately classify different types of anemia is of paramount importance [16]. State-of-the-art approaches in anemia diagnosis using ML and DL encompass a variety of models, including traditional methods like decision trees, random forests, Support Vector Machines (SVM), and neural network-based models such as Multi-Layer Perceptrons (MLP), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) [17]. Each of these models has its strengths and limitations. For instance, CNNs excel at capturing spatial patterns in data, making them suitable for image analysis, while RNNs are adept at handling sequential data, capturing temporal dependencies [18].

Despite the success of these models, there remains a gap in their ability to fully leverage the complex interplay of features in medical datasets [19]. Traditional models often require extensive feature engineering and may struggle with the high dimensionality and heterogeneity of medical data. Pure CNN or RNN models, while powerful, may not capture all relevant patterns when used in isolation [20]. This gap necessitates the exploration of hybrid models that can integrate the complementary strengths of different architectures [21]. In this research, we propose a hybrid CNN-RNN model to diagnose different types of anemia based on CBC data. This model leverages the feature extraction capabilities of CNNs and the sequential processing power of RNNs to improve diagnostic accuracy. By combining these architectures, the hybrid model aims to capture both spatial and temporal patterns in the data, providing a more comprehensive analysis than traditional methods or single architecture models.

Our study compares the performance of the proposed hybrid model with individual DL models, including MLP, CNN, RNN, and Fully Convolutional Networks (FCN). We utilize a labeled dataset containing CBC data and corresponding anemia diagnoses, applying various preprocessing techniques such as feature scaling and label encoding to prepare the data for model training. The evaluation metrics include testing accuracy to assess the models' diagnostic performance. The contributions of this research are manifold. Firstly, we introduce a novel hybrid CNN-RNN model for anemia diagnosis, demonstrating its superior performance over single-architecture DL models. Secondly, we provide a comprehensive comparative analysis of different ML and DL models, highlighting the strengths and limitations of each approach. Thirdly, we emphasize the practical implications of our findings, advocating for the integration of hybrid models in clinical decision support systems to enhance diagnostic accuracy and efficiency. The remaining structure of this article is organized as follows: Section 2 discusses the methodology, including data collection, preprocessing, and model development. In addition, we outline the experimental setup, including the evaluation metrics and cross-validation techniques. Section 3 presents the results and comparative analysis of the models. Finally, Section 4 concludes the article with a summary of contributions and suggestions for future research.

2. RESEARCH METHOD

This section details the comprehensive methodology employed in the research, encompassing data collection, preprocessing, and the development of DL models, including the proposed hybrid CNN-RNN model. The methodology also covers the evaluation metrics and cross-validation techniques used to assess the models' performance.

2.1. Data Collection

The dataset used in this study comprises Complete Blood Count (CBC) data labeled with anemia diagnoses. This data was collected from multiple sources, ensuring a diverse representation of anemia types. The dataset includes several key CBC parameters: Hemoglobin (HGB), Platelet count (PlT), White Blood Cell count (WBC), Red Blood Cell count (RBC), Mean Corpuscular Volume (MCV), Mean Corpuscular Hemoglobin (MCH), Mean Corpuscular Hemoglobin Concentration (MCHC), Platelet Distribution Width (PDW), and Procalcitonin (PCT). The target variable is the type of anemia, diagnosed based on these CBC parameters. Data can be downloaded from [22].

2.2. Data Preprocessing

The preprocessing phase involves several steps to ensure the data is clean, consistent, and suitable for model training. Initially, any missing values are handled through imputation methods or removal, depending on the extent of missingness. The CBC parameters are checked for outliers and anomalies, which are addressed to prevent skewing the model's learning process. Data normalization is performed to scale the numerical features to a standard range, typically using the StandardScaler from the scikit-learn library. This step ensures that the different scales of the CBC parameters do not disproportionately influence the model. Additionally, the categorical target variable, anemia type, is label-encoded to convert it into numerical format, facilitating its use in ML and DL models. For the deep learning models, the target variable is further one-hot encoded to represent it as categorical data. The CBC parameters are checked for outliers and anomalies, which are addressed to prevent skewing the model's learning process. Outliers can be detected using the interquartile range (IQR) method $\text{IQR} = Q3 - Q1$. In addition, $\text{Outlier} = x_{i,j} < Q1 - 1.5 \times \text{IQR}$ or $x_{i,j} > Q3 + 1.5 \times \text{IQR}$, where ($Q1$) and ($Q3$) are the first and third quartiles of the feature distribution.

Data normalization is performed to scale the numerical features to a standard range, typically using the StandardScaler from the scikit-learn library. This normalization is done as $x'_{i,j} = \frac{x_{i,j} - \mu_j}{\sigma_j}$ where $(x'_{i,j})$ is the normalized value, (μ_j) is the mean, and (σ_j) is the standard deviation of the (j) $-$th feature. Additionally, the categorical target variable, anemia type, is label-encoded to convert it into numerical format. This can be represented as $y_i = \text{LabelEncoder}(y_i)$. For the deep learning models, the target variable is further one-hot encoded to represent it as categorical data $y_i = \text{OneHotEncoder}(y_i)$, where (y_i) represents the encoded target variable for the (i)-th sample. One-hot encoding converts the categorical labels into a binary matrix, where each column represents a category. These preprocessing steps ensure that the data is well-prepared for training the ML and DL models, providing a consistent and normalized dataset that can be effectively used to develop robust and accurate anemia diagnosis models.

2.3. Model Development

The research involves developing several models to diagnose anemia types, including single-architecture DL models, and the proposed hybrid CNN-RNN model. The DL models include Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Fully Convolutional Network (FCN). Each model is developed using TensorFlow and Keras, with specific architectures tailored to leverage their strengths. The MLP model consists of several dense layers with dropout and batch normalization to prevent overfitting. The structure of an MLP can be represented as $\text{MLP}(x) = \sigma(W_n \cdot \sigma(W_{n-1} \cdot \ldots \cdot \sigma(W_1 \cdot x + b_1) + b_{n-1}) + b_n)$, where (x) is the input, (W_i) and (b_i) are the weights and biases of the (i)-th layer, and (σ) is the activation function. The CNN model includes convolutional layers for feature extraction, followed by max-pooling and dense layers. The architecture can be described as $\text{CNN}(x) = \sigma(W_c * x + b_c) \rightarrow \text{MaxPooling} \rightarrow \text{Dense layers}$ where (W_c) and (b_c) are the weights and biases of the convolutional layer, \(\ast \) denotes the convolution operation, and MaxPooling is the max-pooling operation. In addition, the RNN model, particularly utilizing LSTM units, captures temporal dependencies in the data. The equations governing an LSTM unit are presented in the equation (1) – (5).

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{1}$$

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{2}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{3}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{4}$$

$$h_t = o_t \cdot \tanh(c_t) \tag{5}$$

where (i_t), (f_t), (o_t), and (c_t) represent the input gate, forget gate, output gate, and cell state, respectively, and (h_t) is the hidden state. The FCN model combines convolutional layers and global average pooling to create an efficient architecture for classification. The global average pooling can be represented as $\text{GlobalAveragePooling}(x) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_{i,j}$, where (H) and (W) are the height and width of the feature map. The hybrid CNN-RNN model integrates the strengths of both CNN and RNN architectures. The model comprises two branches, a CNN branch and an RNN branch. The CNN branch extracts spatial features from the input data through convolutional and pooling layers, followed by flattening. Simultaneously, the RNN branch processes the input through LSTM layers to capture temporal patterns. The outputs of both branches are concatenated and passed through dense layers with dropout and batch normalization before producing the final classification through a softmax layer. The overall architecture can be described as $\text{Hybrid}(x) = \text{Softmax}\left(\text{Dense}\left(\left[\text{Flatten}\left(\text{CNN branch}(x)\right), \text{RNN branch}(x)\right]\right)\right)$ and also we describe the architecture of the model in figure 1.

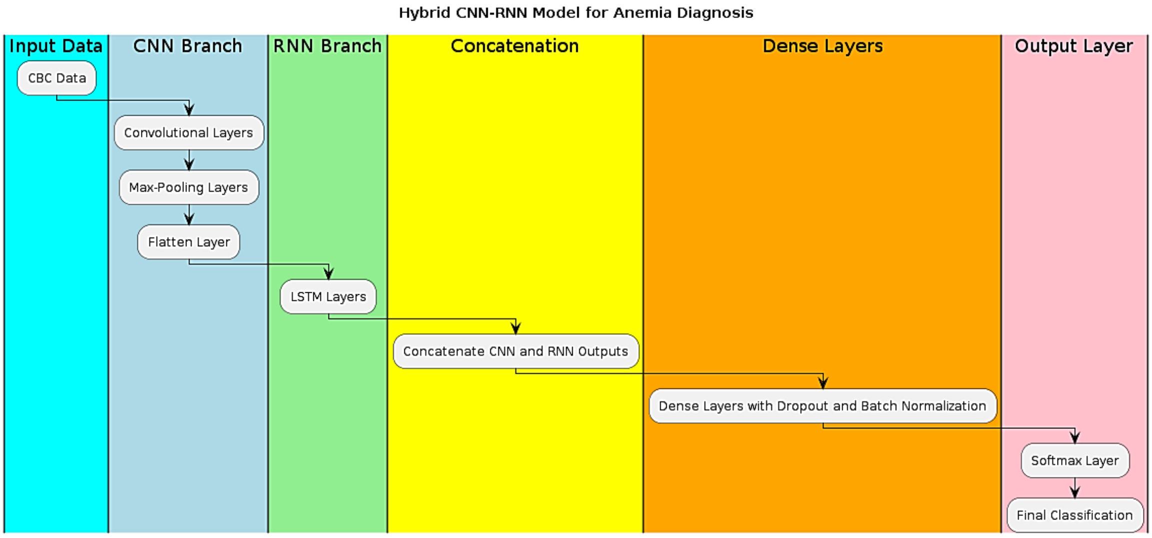


Figure 1. Hybrid CNN-RNN Model

2.4. Cross-Validation and Model Training

To ensure robust model evaluation, stratified k-fold cross-validation is employed. The dataset is split into training and validation sets in a stratified manner, preserving the proportion of each anemia type in each fold. This approach mitigates the risk of overfitting and provides a reliable estimate of the models' performance. To ensure robust model evaluation, stratified k-fold cross-validation is employed. The dataset is split into training and validation sets in a stratified manner, preserving the proportion of each anemia type in each fold. This approach mitigates the risk of overfitting and provides a reliable estimate of the models' performance. Mathematically, for a dataset (D) with (n) samples, stratified k-fold cross-validation involves dividing (D) into (k) subsets $(D_1, D_2, \ldots, D_k)$ such that the proportion of each class is approximately the same in each subset. For each fold (i), the model is trained on $(D \setminus D_i)$ and validated on (D_i). During model training, several hyperparameters, including learning rate $((\alpha))$, batch size $((m))$, and the number of epochs $((E))$, are tuned. The models are trained using the Adam optimizer, known for its efficiency and ability to adapt the learning rate during training. The Adam optimizer updates the model parameters based on the following equations (6) – (10).

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{6}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{7}$$

$$\widehat{m_t} = \frac{m_t}{1 - \beta_1^t} \tag{8}$$

$$\widehat{v_t} = \frac{v_t}{1 - \beta_2^t} \tag{9}$$

$$\theta_{t+1} = \theta_t - \alpha \frac{\widehat{m_t}}{\sqrt{\widehat{v_t}} + \epsilon} \tag{10}$$

where (m_t) and (v_t) are the first and second moment estimates, (β_1) and (β_2) are the decay rates for the moment estimates, (g_t) is the gradient at time step (t), $(\widehat{m_t})$ and $(\widehat{v_t})$ are the bias-corrected estimates, and (θ_t) represents the model parameters. The categorical cross-entropy loss function is used for optimization, appropriate for multi-class classification problems. The categorical cross-entropy loss (L) for a single sample is given by $L = -\sum_{c=1}^{C} y_c \log(\widehat{y_c})$, where (C) is the number of classes, (y_c) is the true label (one-hot encoded), and $(\widehat{y_c})$ is the predicted probability for class (c). These techniques ensure that the models are trained and evaluated in a robust manner, providing reliable performance metrics and reducing the risk of overfitting.

2.5. Evaluation Metrics

The performance of the models is evaluated using multiple metrics to provide a comprehensive assessment. The primary metric is accuracy, measuring the proportion of correctly classified instances. Balanced accuracy is also considered, particularly important in datasets with class imbalance, as it accounts for the performance across all classes. Confusion matrices are generated to visualize the performance of each model in classifying different anemia types. These matrices provide insights into the models' strengths and weaknesses in distinguishing between various classes. In addition, test accuracy can be described as $\text{Accuracy} = \frac{\text{Number of correctly classified instances}}{\text{Total number of instances}} = \frac{TP+TN}{TP+TN+FP+FN}$, where *TP* is the number of true positives, *TN* is the number of true negatives, *FP* is the number of false positives, and *FN* is the number of false negatives.

2.6. Comparative Analysis

A comparative analysis is conducted to evaluate the performance of the proposed hybrid CNN-RNN model against traditional ML models and single-architecture DL models. This analysis involves comparing the accuracy, balanced accuracy, and confusion matrices of each model. The strengths and limitations of each approach are discussed, highlighting the advantages of the hybrid model in capturing complex patterns in the CBC data. The models are also evaluated on the test set, ensuring that the findings generalize to unseen data. The test set evaluation includes generating confusion matrices and classification reports, providing a final assessment of the models' diagnostic capabilities.

3. RESULTS AND ANALYSIS

The performance of various models for anemia diagnosis was evaluated using metrics such as cross-validation accuracy, test accuracy as presented in the table 1. These findings offer a detailed comparison between single-architecture deep learning models, and the proposed hybrid CNN-RNN model. In terms of cross-validation accuracy, the 5-fold results for each model were as follows: the Multilayer Perceptron (MLP) achieved 81.05% with a standard deviation of 1.90%, the Convolutional Neural Network (CNN) reached 87.99% with a standard deviation of 1.81%, the Recurrent Neural Network (RNN) had 76.85% with a higher standard deviation of 3.08%, the Fully Convolutional Network (FCN) recorded 87.01% with a standard deviation of 2.86%, and the hybrid CNN-RNN model achieved 87.31% with a standard deviation of 1.77%. The CNN model had the highest cross-validation accuracy, closely followed by the hybrid CNN-RNN and the FCN models. The MLP showed moderate performance, while the RNN exhibited the lowest accuracy and higher variability, indicating instability across different folds.

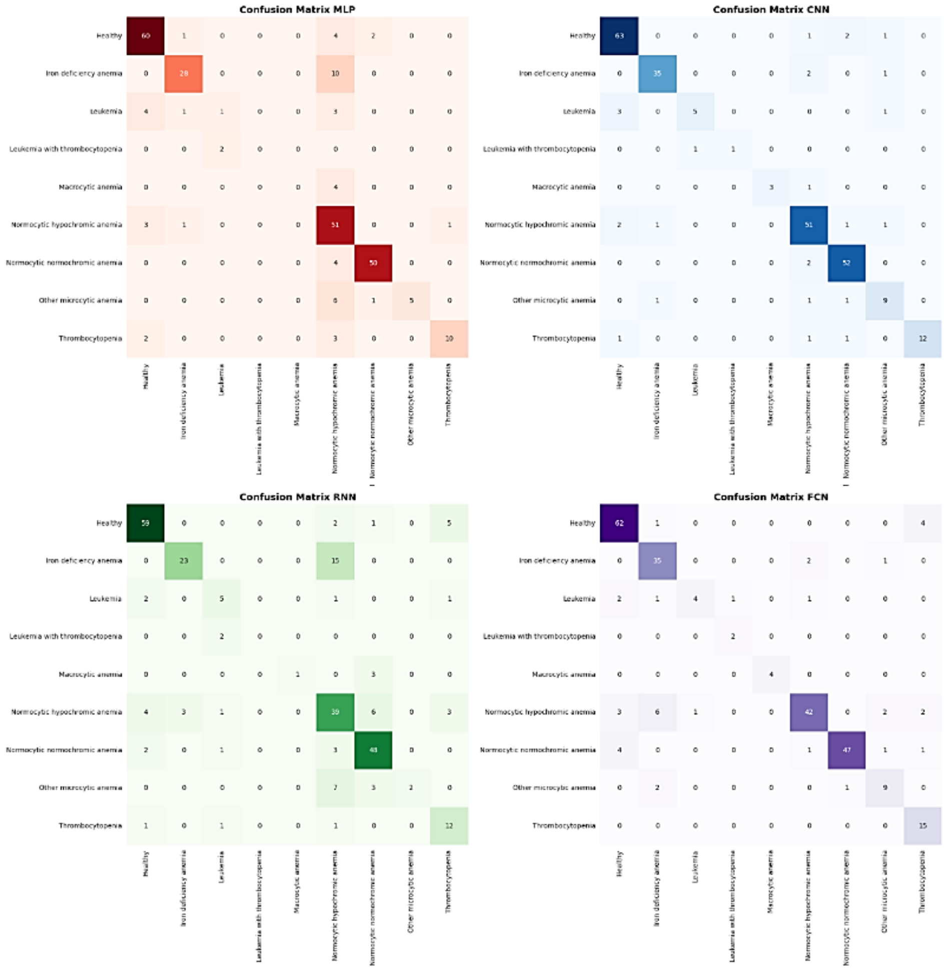
For test accuracy, the performance on the hold-out test set revealed that the hybrid CNN-RNN model outperformed all others with an accuracy of 90.27%. The CNN model followed closely with 89.88%, demonstrating robust generalization to unseen data. The FCN model also performed competitively with an accuracy of 85.60%. In contrast, the MLP and RNN models had lower test accuracies of 79.77% and 73.54%, respectively, with the RNN particularly struggling with the test data, reflecting its lower cross-validation accuracy. The confusion matrices offered deeper insights into the models' performance in classifying different types of anemia. Precision and recall metrics were not specifically included in this experiment due to the nature of the dataset and the focus on overall classification accuracy. In medical diagnostics, the primary objective is often to maximize overall accuracy and minimize the risk of misdiagnosis. The cross-validation accuracy and test accuracy provided a comprehensive assessment of each model's performance, considering both true positive and true negative rates. However, future studies could benefit from incorporating these metrics to gain additional insights into the balance between false positives and false negatives, especially in scenarios where the cost of misclassification is significant. The MLP model showed moderate performance but struggled with accurately classifying normocytic normochromic anemia and other microcytic anemia, as evidenced by significant misclassifications. It also had difficulty distinguishing between iron deficiency anemia and other classes. On the other hand, the CNN model demonstrated high accuracy across all classes, excelling particularly in classifying healthy cases and normocytic normochromic anemia. The spatial pattern recognition capabilities of CNNs contributed to its superior performance, although some misclassifications occurred with iron deficiency anemia and other microcytic anemia.

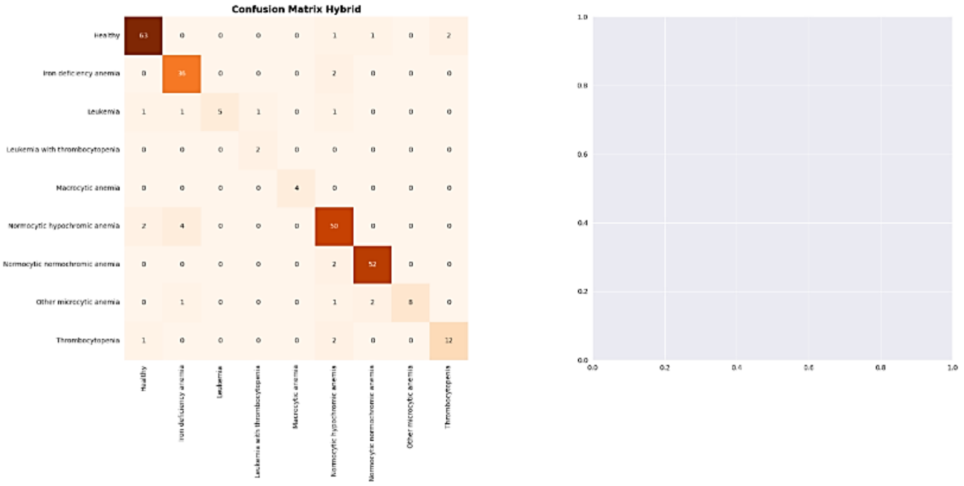
Table 1. The Performance of Machine Learning Models

Model	Cross-Validation Accuracy (Mean ± SD)	Test Accuracy
MLP	0.8105 ± 0.0190	0.7977
CNN	0.8799 ± 0.0181	0.8988
RNN	0.7685 ± 0.0308	0.7354
FCN	0.8701 ± 0.0286	0.8560
Hybrid CNN-RNN	0.8731 ± 0.0177	0.9027

The RNN model exhibited notable misclassifications, especially in distinguishing between normocytic normochromic anemia and normocytic hypochromic anemia. The sequential nature of the data did not provide a significant advantage for the RNN model in this context, as reflected in its lower overall accuracy. Conversely, the FCN model performed well, with high accuracy in most classes, excelling in classifying healthy cases and iron deficiency anemia but encountering some difficulty with normocytic normochromic anemia, similar to the MLP model. The hybrid CNN-RNN model achieved the highest accuracy, demonstrating robust performance across all classes. By combining the spatial feature extraction capabilities of CNNs with the temporal processing power of RNNs, the hybrid model improved classification accuracy significantly. It showed fewer misclassifications compared to the other models, excelling particularly in classifying normocytic normochromic anemia and iron deficiency anemia. These results highlight that the hybrid CNN-RNN model provides superior performance in diagnosing different types of anemia compared to traditional ML models and single-architecture DL models. The integration of CNN and RNN architectures allows the hybrid model to capture both spatial and temporal patterns in the Complete Blood Count (CBC) data, enhancing its diagnostic accuracy. The CNN model's exceptional performance underscores the effectiveness of convolutional layers in extracting relevant features from the data. The FCN model's competitive performance suggests that combining convolutional layers with global average pooling is a viable approach for medical diagnostics.

The MLP and RNN models showed lower accuracy, indicating they might not be as well-suited for this classification task. The MLP model's performance could potentially be improved with more sophisticated feature engineering, while the RNN model's sequential processing did not provide a significant advantage for this dataset. The confusion matrices as presented in the figure 2 reveal specific strengths and weaknesses of each model. The hybrid CNN-RNN model's robust performance across all classes and fewer misclassifications underscore the potential of hybrid models in enhancing diagnostic accuracy for complex medical datasets. Overall, the study emphasizes the importance of leveraging advanced deep learning architectures, such as hybrid models, to improve the accuracy and reliability of medical diagnostics. The proposed hybrid CNN-RNN model shows significant promise for anemia diagnosis, offering a valuable tool for clinical decision support systems. Future research could explore further refinements to the hybrid model, such as incorporating attention mechanisms or additional feature engineering, to enhance its performance further.





Confusion Matrix Hybrid

	Healthy	Iron deficiency anemia	Leukemia	Leukemia with thrombocytopenia	Macrocytic anemia	Normocytic hypochromic anemia	Normocytic normochromic anemia	Other microcytic anemia	Thrombocytopenia
Healthy	63	0	0	0	0	1	1	0	2
Iron deficiency anemia	0	36	0	0	0	2	0	0	0
Leukemia	1	1	5	1	0	1	0	0	0
Leukemia with thrombocytopenia	0	0	0	2	0	0	0	0	0
Macrocytic anemia	0	0	0	0	4	0	0	0	0
Normocytic hypochromic anemia	2	4	0	0	0	50	0	0	0
Normocytic normochromic anemia	0	0	0	0	0	2	52	0	0
Other microcytic anemia	0	1	0	0	0	1	2	8	0
Thrombocytopenia	1	0	0	0	0	2	0	0	12

Figure 2. Confusion Matrix of Methods

4. CONCLUSION

This research aimed to develop and evaluate various deep learning (DL) models for the accurate diagnosis of different types of anemia based on complete blood count (CBC) data. The models tested included traditional ML models (e.g., decision trees, random forests, support vector machines), single-architecture DL models (e.g., multi-layer perceptron, convolutional neural network, recurrent neural network, fully convolutional network), and a novel hybrid CNN-RNN model. The hybrid model integrated the spatial feature extraction capabilities of CNNs with the sequential processing power of RNNs. The findings indicate that the hybrid CNN-RNN model achieved the highest accuracy among all tested models, both in cross-validation and on the test set. The hybrid model's superior performance demonstrates its ability to capture complex patterns in CBC data, leading to more accurate anemia diagnosis. The CNN model also performed exceptionally well, highlighting the effectiveness of convolutional layers in extracting relevant features from the data. The FCN model showed competitive performance, suggesting that it is a viable approach for medical diagnostics. In contrast, the MLP and RNN models had lower accuracies, indicating that they may not be as well-suited for this classification task without further refinement.

The confusion matrices provided detailed insights into the models' performance across different anemia types. The hybrid CNN-RNN model exhibited fewer misclassifications compared to the other models, demonstrating its robustness and reliability. This model effectively distinguished between various types of anemia, including normocytic normochromic anemia and iron deficiency anemia, which were particularly challenging for the other models. The urgency of this research lies in the global burden of anemia, which demands efficient and accurate diagnostic tools to facilitate timely intervention. The hybrid CNN-RNN model, with its superior performance, addresses this need by providing a more accurate and reliable diagnostic tool. The study underscores the potential of advanced DL architectures, especially hybrid models, in enhancing the accuracy and reliability of medical diagnostics. The proposed hybrid CNN-RNN model offers a valuable tool for clinical decision support systems, aiding healthcare professionals in making timely and accurate diagnoses. Future research could explore further refinements to the hybrid model, such as incorporating attention mechanisms or additional feature engineering, to enhance its performance. Additionally, the application of this hybrid approach to other medical datasets could validate its generalizability and robustness in various diagnostic contexts. The integration of such models into clinical practice has the potential to significantly improve patient outcomes by facilitating early and accurate diagnosis of anemia and other medical conditions.

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