iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 **Issue:** XI **Month of publication:** November 2023

DOI: https://doi.org/10.22214/ijraset.2023.56719

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue XI Nov 2023- Available at www.ijraset.com

Machine Learning Driven Anemia Identification and Classification: A Comprehensive Survey

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Abstract: Anemia, a common medical condition characterized by a deficiency in red blood cells or hemoglobin, presents a significant health concern globally. The development of accurate and efficient tools for the identification and classification of anemia is crucial for early diagnosis and targeted intervention. Machine learning, with its robust capabilities in pattern recognition, has emerged as a promising avenue for addressing this challenge. This literature survey paper provides a comprehensive overview of existing research in the field of anemia identification and classification using machine learning.
The paper begins by delineating the epidemiological significance of anemia, underlining the pressing need for advanced diagnostic techniques. A systematic examination of the physiological basis of anemia, its types, and clinical symptoms sets the stage for understanding the complexity of anemia classification. We review traditional diagnostic methods and their limitations, emphasizing the potential for machine learning to augment and enhance these techniques.
The primary objective of this survey is to synthesize existing knowledge in the field, identify common trends, and highlight advancements that have significantly contributed to the accuracy and efficiency of RBC classification methods. The survey is organized into several key sections, each exploring distinct aspects of previous research endeavors.
The survey commences with an overview of the importance of RBC classification in medical diagnostics, emphasizing the critical role of automated techniques in improving efficiency and accuracy. It then delves into the fundamentals of image processing and CNNs, providing a foundation for understanding the methodologies discussed in subsequent sections.
The core of the survey is dedicated to a comprehensive analysis of previous implementations, categorizing them based on their proposed models and datasets. Each section provides a detailed review of the methodology, highlighting the key contributions and innovations, and the datasets used for training and evaluation. Specific areas of focus include feature extraction techniques, network architectures, and classification algorithms employed in these projects.
Furthermore, the survey addresses challenges encountered in RBC classification, such as dataset scarcity, class imbalance, and the need for robust and interpretable models. It also explores the potential for transfer learning and the integration of emerging technologies like deep learning and edge computing in this domain.
In conclusion, this paper not only illuminates the advancements made in anemia detection but also underscores the gaps and opportunities for further research. It provides a valuable resource for researchers, medical practitioners, and data scientists seeking to enhance the accuracy and efficiency **of RBC classification systems, ultimately contributing to the improvement of medical diagnostics and patient care.**
Keywords: Anemia, Classification, Machine Learning, Convolutional Neural Network (CNN), Algorithm Comparison, Image Processing, Red Blood Cells (RBC),

I. INTRODUCTION

Anemia, a condition characterized by a deficiency in red blood cells or hemoglobin, has persisted as a global health challenge affecting millions of individuals worldwide. One-fourth of the global population is estimated to be anemic, with cases increasing rapidly for women, expectant mothers, young girls, and children younger than age 5. In 2021, 1.92 billion people globally had anemia. This is an increase of 420 million cases over three decades. Between 1990 and 2021, the study shows a global shift toward less severe anemia. The largest decreases were in adult males, with slower rates of progress among women of reproductive age and children younger than age 5. Anemia is also the third-leading cause of years with lived disability (YLDs) in the world. In India, the problem is particularly serious as the statistics show that anemia is prevalent in 57.0 percent in women (15-49 years), 31.1 percent in adolescent boys (15-19 years), 59.1 percent in adolescent girls, 52.2 percent in pregnant women (15-49 years) and 67.1 percent in children (6-59 months). Anemia represents a complex and multifaceted medical disorder that can result from various underlying causes, ranging from nutritional deficiencies to chronic diseases.

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Timely and accurate identification and classification of anemia are vital steps in its management and treatment. In this era of rapid technological advancement, machine learning has emerged as a powerful tool to aid healthcare professionals in the diagnosis and classification of anemia.

When examining a microscopic image of blood samples, several distinct effects of anemia on red blood cells can be observed. These morphological changes are helpful in detecting anemia and identifying its underlying causes. Anemia often leads to a variation in the size of red blood cells. This condition is known as anisocytosis, and it is characterized by the presence of both smaller (microcytic) and larger (macrocytic) RBCs in the same sample. It can also result in irregular RBC shapes, a condition known as poikilocytosis. This can lead to the presence of abnormally shaped RBCs, such as teardrop cells (dacrocytes), target cells (codocytes), and sickle-shaped cells (in sickle cell anemia). It also leads to hypochromia, a condition where RBCs have a reduced amount of hemoglobin, leading to a pale or central pallor. In a microscopic image, hypochromic RBCs appear less red and more translucent in the center, which is a characteristic feature of conditions like iron deficiency anemia.

Traditional methods of detecting anemia include Complete Blood Count (CBC), hemoglobin electrophoresis, reticulocyte count, bone marrow tests, and serum ferritin tests. A CBC is one of the most common and fundamental tests for diagnosing anemia and provides information about the number of red blood cells (RBCs), hemoglobin levels, hematocrit (the percentage of blood composed of RBCs), mean corpuscular volume (MCV), mean corpuscular hemoglobin (MCH), and mean corpuscular hemoglobin concentration (MCHC). Hemoglobin electrophoresis is used to identify abnormal types of hemoglobin, such as in the case of sickle cell anemia and thalassemia. Reticulocytes are young, immature red blood cells. A reticulocyte count measures the percentage of these cells in the blood. A high reticulocyte count indicates that the bone marrow is actively producing red blood cells in response to anemia. These methods usually take a long time, are expensive, and require expert knowledge of the field. Application of machine learning in this field can lead to faster diagnosis of anemia that is cheap and free from human error.

With the ability to process vast amounts of data, recognize complex patterns, and make accurate predictions, machine learning offers new perspectives and solutions for anemia-related challenges. The limitations of conventional diagnostic methods are highlighted to underscore the pressing need for innovative approaches. Traditional laboratory tests and diagnostic criteria, while valuable, are not infallible and can be further augmented by leveraging machine learning's potential. This paper seeks to draw attention to the current advancements in the use of machine learning in diagnosing anemia in contrast to the traditional methods. This paper will review each method that uses machine learning to diagnose anemia and discuss its merits and demerits.

II. LITERATURE REVIEW

Leveraging the immense capabilities of data-driven algorithms, machine learning offers an opportunity to enhance the precision and reliability of anemia diagnosis, thus transforming the landscape of healthcare for individuals affected by this condition. Our focus will be on the remarkable potential of machine learning algorithms, which have been designed to complement and enhance traditional techniques, revolutionizing anemia diagnosis in the process.

Reference [24] proposed a non-invasive method of anemia classification using a multi-wavelength photometry sensor and a novel classification algorithm based on hierarchical ensemble classifiers. They leveraged recent advancements in machine learning to develop a non-invasive approach for estimating the clinical severity of anemia.

Reference [28] utilized holographic microscopy and hierarchical machine learning classifiers to perform the differential diagnosis of hereditary anemias. They developed a hierarchical machine learning classifier to identify the presence of anemia and predict the specific type of anemia among five phenotypes.

Reference [26] investigated the detection of iron deficiency anemia using machine learning models. They compared the performance of machine learning algorithms in analyzing images of fingernails, palms, and conjunctiva of the eye for the detection of iron deficiency anemia.

Reference [6] focuses on developing an Anemia Cells Recognition System using Raspberry Pi. The system employs image processing and support vector machine (SVM) for the classification of abnormal red blood cells (RBCs). The automated recognition achieves an average accuracy of 94.31%, contributing to the advancement of anemia and thalassemia detection.

Reference [7] introduces a 3-Tier Deep Neural Network for identifying anemia and determining its severity level in peripheral blood smears. The proposed model achieves high accuracies in training (91.37%), validation (88.85%), and testing (86.06%), with recall, F1-Score, and specificity metrics demonstrating its effectiveness in anemia severity prediction.

Reference [8] explores the use of a Convolutional Neural Network (CNN) for classifying hemoglobin levels based on palm images. Achieving an accuracy of 96.43%, this study offers a non-invasive alternative to traditional blood tests, emphasizing the potential of CNN in anemia detection.

Reference [9] presents a machine learning system utilizing deep learning technology to predict anemia using facial images. With accuracies ranging from 82.37% to 74.01% for different anemia severity levels, the system proves valuable in expediting diagnosis and aiding in urgent blood transfusion decisions in emergency departments.
Reference [27] employed various machine learning algorithms, including artificial neural networks, K-nearest neighbors, random forests, naive Bayes, and support vector machines, for the diagnosis of anemia in an outpatient clinical setting. They compared the performance of these algorithms in classifying anemia and malaria.
Reference [10] focuses on the detection of anemia using image processing techniques from microscopy blood smear images. The proposed algorithm achieves an accuracy of 93.33%, with specificity and sensitivity values of 95.16% and 90.91%, respectively, showcasing its potential for automated RBC counting in anemic conditions.
Reference [11] introduces the application of artificial intelligence, specifically K-nearest neighbors (KNN), in the diagnosis and classification of anemia. The study emphasizes the significance of monitoring parameters like age, sex, and various blood parameters in accurate anemia diagnosis.
Reference [12] proposes a curability prediction model for anemia using supervised machine learning techniques, including Naive Bayes, Logistic Regression, LASSO, and ES algorithms. The study aims to predict the cure or non-cure status of patients after 90 days, with Naive Bayes exhibiting superior accuracy.
Reference [13] estimates blood parameters in anemic children patients, emphasizing gender and age as factors influencing anemia. The study reveals deteriorated hematological variables in anemic children, with males and children under three years being more affected.
Reference [15] employs data mining techniques to predict anemia, comparing Bayesian Network, Naive Bayes, Logistic Regression, and Multilayer Perceptron. Logistic Regression and Multilayer Perceptron demonstrate high performance, with the study highlighting their efficiency in predicting anemia.
Reference [19] investigates machine learning models for predicting anemia, comparing five different algorithms and highlighting the potential of machine learning in improving disease prevention and treatment.
Reference [16] focuses on anemia prediction based on rule classification, utilizing techniques like ZeroR, OneR, and PART. The PART technique achieves the highest accuracy of 85%, showcasing its potential for creating accurate anemia prediction systems.
Reference [25] focused on the classification of red blood cells in microscopy images to aid in the diagnosis of sickle cell anemia. The researchers proposed three CNN models with different layers and filters. They utilized image processing and machine learning techniques to classify, count, and segment sickle cell anemia in erythrocytes.
Reference [14] compares Decision Tree, SVM, and KNN for predicting anemic conditions. By analyzing conjunctiva color and blood hemoglobin levels, the study achieves an 82.61% accuracy in Decision Tree classification.
Reference [17] develops a model for predicting anemia in children under 5 years of age using machine learning algorithms, with Random Forest proving to be the best performer with an accuracy of 98.4%.
Reference [22] classifies anemia types using artificial learning methods, achieving high accuracy with Bagged Decision Trees, Boosted Trees, and Artificial Neural Networks.
Reference [23] discusses the role of data mining techniques in predicting anemia, using classification techniques like J48, Random Forest tree, and Hoeffding tree, with Random Forest tree exhibiting better accuracy.
Reference [5] focuses on emerging point-of-care technologies for anemia detection, emphasizing the need for accessible and cost-effective screening methods, especially in low- and middle-income countries.
In Reference [4], the study assesses Naive Bayes, random forest, and decision tree algorithms using CBC data. The results show Naive Bayes outperforming the others with an accuracy of 96.09%. The numerical values for random forest accuracy (95.32%) and decision tree accuracy (95.46%) provide a quantitative basis for comparison.
The research in Reference [3] addresses the challenges of manual inspection. The comparison of machine learning classifiers reveals that Naive Bayes has lower precision, recall, f-score, and accuracy compared to SVM, random forest, and logistic regression. SVM and logistic regression both have 90% accuracy, while random forest achieves 92%.
Reference [2] introduces five ensemble learning methods applied to four classifiers. The stacking method achieves the highest accuracy, outperforming Bagging, Voting, Adaboost, and Bayesian Boosting. Individual classifiers' performance is also assessed, with Artificial Neural Network (ANN) leading, and K-Nearest Neighbor (K-NN) performing the worst.
Finally, Reference [1] combines image processing and CNN to achieve an overall accuracy of 98.5%. The study focuses on classifying RBCs into nine types, showcasing the potential of the proposed method for accurate disease diagnosis.

TABLE I
COMPARATIVE ANALYSIS

Paper Title	Methodology	Accuracy/Performance	Dataset Used
Development of Anemia Cells Recognition System Using Raspberry Pi	Image processing, SVM	94.31%	Blood smear images
Identification of Anemia and Its Severity Level in a Peripheral Blood Smear Using 3-Tier Deep Neural Network	3-tier deep convolutional fused network	Training: 91.37% Validation: 88.85% Test: 86.06%	Shaukat Khanum Hospital and Research Center (SKMCH&RC), Pakistan.
Detecting Anemia Based on Palm Images using Convolutional Neural Network	Convolutional Neural Network (CNN)	Cluster 1: 96.43%, Cluster 2: 96.43%	Soebandi General Hospital, Jember Regency, Indonesia
Prediction of anemia using facial images and deep learning technology in the emergency department	Convolutional Neural Networks	82.37%	Video data of 316 patients from Chinese PLA General Hospital First Central Division
Detection of Anaemia using Image Processing Techniques from microscopy blood smear images	Image processing	Accuracy: 93.33%, Specificity: 95.16%, Sensitivity: 90.91%	Apollo Hospital
Curability Prediction Model for Anemia Using Machine Learning	Supervised ML (Naive Bayes, LR, LASSO, ES)	NaiveBayes outperforms others in terms of accuracy	CBC data from pathology centers
Analysis of Anemia Using Data Mining Techniques with Risk Factors Specification	Bayesian Network, Naive Bayes, Logistic Regression and Multilayer Perceptron	LR and MLP show better performances with accuracies: 86.1%	Data from laboratories with 10 attributes
Anemia Prediction Based on Rule Classification	Rule Classification (ZeroR, OneR, PART)	PART provides 85% accuracy higher than OneR and ZeroR	A dataset of 539 participants with 10 features
Comparative Study Between Decision Tree, SVM, and KNN to Predict Anaemic Condition	Image processing, Classification (Decision Tree, SVM, KNN)	Decision Tree (Coarse) achieves 82.61% accuracy	Clinical blood hemoglobin level and palpebral conjunctiva images
Prediction of Anemia Using Machine Learning Algorithms	Random Forest, Decision Tree, Naïve Bayes, Artificial Neural Network, Support Vector Machine and Logistic Regression	Random Forest achieves 98.4% accuracy	Data from Kanti Children Hospital-700 data records
A Harmful Disorder: Predictive and Comparative Analysis for Fetal Anemia Disease by Using Different Machine Learning Approaches	K-Nearest Neighbors, Logistic Regression, Support Vector Machines, Gaussian Naive Bayes, and Light Gradient Boosting Machines	The voting classifier achieved 99.95% accuracy	Not specified

Classifying Anemia Types Using Artificial Learning Methods	Artificial Learning (ANN, SVM, Naive Bayes, Ensemble Decision Tree)	Accuracy: Bagged Decision Trees (85.6%), Boosted Trees (83.0%), ANN (79.6%)	A dataset of 1663 samples with 25 attributes from a university hospital in Turkey
A Role of Data Mining Techniques to Predict Anemia Disease	Data Mining (J48, Random Forest tree, Hoeffding tree)	Random Forest tree shows better accuracy at 97.57%	206 household of students from Public Health College in Jazan University
Anemia detection using ensemble learning techniques and statistical models	Decision Tree, Artificial Neural Network, Naïve Bayes and K-Nearest Neighbor with Stacking, Bagging, Voting, Adaboost and Bayesian Boosting	The stacking method has proven superior to all the other four ensemble methods by achieving the highest precision, recall, accuracy and specificity by using a combination of K-NN and Decision tree as base learners and Naïve Bayes as stacking learner	50 blood smear slides were collected from Goa Medical College – Bambolim Goa
Machine Learning based Diagnosis and Classification of Sickle Cell Anemia in Human RBC	Naïve Bayes, Random Forest, SVM, Logistic Regression	SVM, LR: 90% Random Forest: 92% Naïve Bayes: 88%	Special hematology department of the general hospital from Santiago de Cube

In summary, these research papers collectively demonstrate the diverse approaches and technologies employed in the detection, classification, and prediction of anemia. The studies range from traditional image processing techniques to advanced deep learning and machine learning algorithms, showcasing the interdisciplinary nature of anemia research.

They demonstrate the potential of machine learning algorithms in the identification and classification of anemia. By leveraging advancements in image processing, sensor technologies, and classification algorithms, machine learning approaches can provide non-invasive and efficient methods for diagnosing and classifying anemia. These techniques have the potential to improve the accuracy and speed of anemia diagnosis, enabling timely interventions and personalized treatment strategies.

III. PROPOSED METHODOLOGY

A. Data Collection

In the imminent stages of our research, a meticulous process of data collection will ensue, seeking to construct a robust and diverse dataset representative of various blood parameters associated with anemia. This dataset will be curated with an emphasis on inclusivity, encompassing demographic factors such as age groups, genders, and ethnicities. The dataset consisting of microscopic blood smear images of distinct patients will be acquired from the local hospital. We will also be using online available open-source datasets such as BCCD and others.

B. Data Preprocessing

In the initial phase of the research, specific attention will be devoted to the preprocessing of the image dataset, aiming to enhance the quality and suitability of the visual data for subsequent analysis. The images, representing peripheral blood smears or relevant visual indicators of anemia, will undergo a series of preprocessing steps tailored for image data.

1) *Image Enhancement and Transformation:* The raw images will be subjected to enhancement techniques, including contrast adjustments and histogram equalization, to improve visibility and accentuate features crucial for anemia classification.

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Additionally, geometric transformations such as rotation and scaling may be applied to augment the dataset and ensure model robustness.

2) *Normalization and Standardization:* Pixel values within the images will be normalized and standardized to ensure uniformity in intensity levels. This step is essential for mitigating variations in illumination conditions across different images, contributing to the overall reliability of the image dataset.
3) *Noise Reduction and Filtering:* To enhance the signal-to-noise ratio, noise reduction algorithms and filters, such as Gaussian or median filters, may be employed. This is particularly crucial in the context of blood smear images, where subtle abnormalities indicative of anemia need to be accurately discerned.
4) *Image Segmentation*: For precise identification of relevant regions of interest within the images, segmentation techniques will be applied. This involves partitioning the image into distinct regions and isolating specific elements such as red blood cells or anomalies associated with anemia.
5) *Handling Missing or Corrupted Image Data:* Addressing missing or corrupted image data is imperative for maintaining dataset integrity. Strategies like data imputation or, when appropriate, removal of unusable images will be implemented to ensure a robust image dataset for subsequent model development.
6) *Augmentation for Data Diversity:* To enhance the diversity of the image dataset and improve model generalization, data augmentation strategies will be employed. This may involve introducing variations in image orientation, flipping, or introducing controlled distortions, effectively expanding the dataset for more comprehensive training.
7) *Quality Control and Annotation*: Every effort will be made to ensure the quality and accuracy of image annotations. Annotations, indicating regions of interest or specific features relevant to anemia classification, will be meticulously reviewed to minimize annotation errors and discrepancies

C. Feature Selection

A pivotal step in our methodology involves the strategic selection of features that are indicative of either iron deficiency or vitamin deficiency anemia. This feature selection process will employ techniques such as feature importance ranking and correlation analyses, aiming to identify the most pertinent indicators for anemia classification. By focusing on informative features, the subsequent model will be constructed on a foundation of relevance and clinical significance.

D. Dataset Splitting

After feature selection, the dataset will be judiciously split into training, validation, and test sets in the upcoming phases. This strategic partitioning is crucial for the effective training, validation, and evaluation of our machine-learning models. The training set will serve as the cornerstone for model development, while the validation set will facilitate fine-tuning to prevent overfitting. The test set, representing unseen data, will be instrumental in assessing the model's generalization capabilities.

E. Algorithm Selection

Given the nature of the dataset consisting of microscopic blood smear images, Convolutional Neural Networks (CNNs) emerge as the most suitable algorithm for anemia classification. CNNs are adept at capturing intricate spatial features within images, making them ideal for discerning subtle patterns indicative of iron deficiency or vitamin deficiency anemia in blood cells.

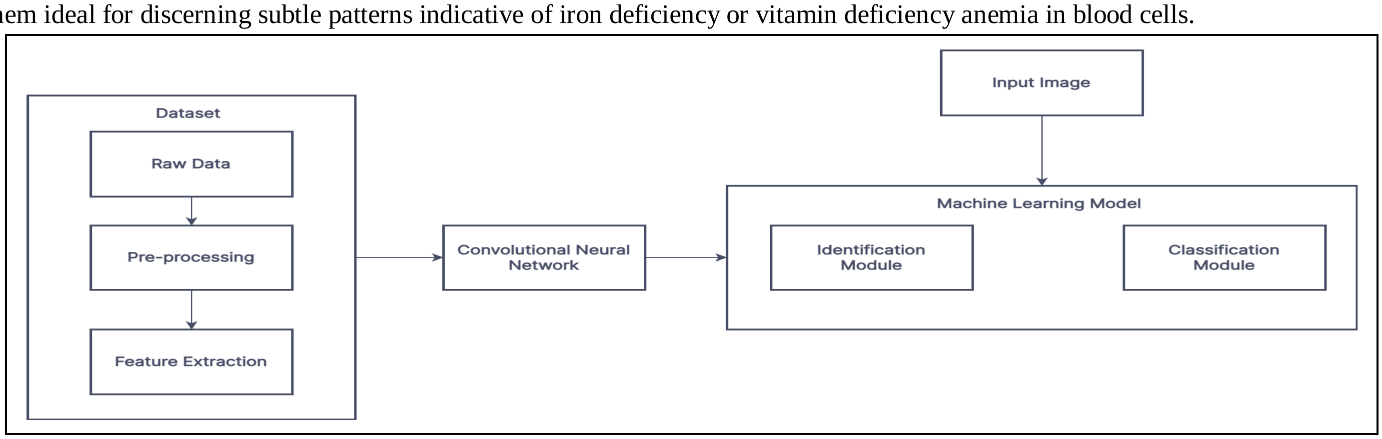


Fig. 1 Architecture of Proposed System

F. Model Training

Once the algorithms are chosen, they will undergo extensive training using the designated training dataset in the future. Hyperparameter optimization will be conducted to enhance model performance. Hyperparameters specific to the CNN architecture, such as learning rate, dropout rates, and batch sizes, will be fine-tuned to optimize the model's performance on the microscopic blood smear image dataset. This iterative process aims to achieve the most effective configuration for accurate anemia classification. This training phase will be iterative, allowing for continuous refinement of the machine learning models. The CNN model architecture will be meticulously designed, incorporating convolutional layers to extract hierarchical features from the microscopic blood smear images. Pooling layers will be integrated for spatial down-sampling, and fully connected layers will facilitate the final classification based on the learned features.

G. Model Evaluation

Following the training phase, the models will undergo meticulous evaluation using the validation dataset. Performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC will be employed to assess the efficacy of each model in capturing the nuances of anemia classification. Rigorous evaluation criteria will be established to ascertain the model's predictive capabilities.

H. Testing Phase

Once the models are trained, and validated, and class labels are defined, they will undergo testing using the designated test dataset in the future. This testing phase is imperative for gauging the generalization capabilities of our CNN model and validating its predictive performance against real-world scenarios.

I. Interpretability Considerations

Interpretability techniques tailored for CNNs, such as layer-wise relevance propagation or gradient-based methods, will be employed to elucidate the features contributing to the model's predictions. This ensures a transparent understanding of the CNN's decision-making process.

J. Model Deployment

Deployment of the trained model into a system accessible to healthcare professionals will be a culmination of our future efforts. The trained model will be deployed on a web application for use by healthcare professionals. Continuous monitoring mechanisms will be implemented, allowing for adaptability to changing data patterns and facilitating updates to incorporate new medical insights.

K. User Interface Design

To facilitate seamless interaction between healthcare professionals and our web application, a user-friendly interface will be meticulously designed. Visualizations and explanations will be integrated to enhance the interpretability of the system outputs, fostering effective communication between the model and end-users.

L. Collaboration with Medical Professionals

Collaboration with medical professionals will be an ongoing thread throughout our system development. Consultation with doctors from the local hospital will be a continuous process and will help us in validation of the system's predictions against real-world patient data and adherence to healthcare standards.

IV. DATASET

The dataset for our anemia detection system will be meticulously curated from local hospitals, emphasizing manual labeling to ensure accuracy and reliability in the diagnostic information. By collaborating with healthcare professionals, we aim to capture a diverse range of cases, considering factors such as age, gender, and ethnicity, mirroring the real-world scenarios encountered in clinical settings. Additionally, to augment our dataset and provide further robustness to our model, we will supplement local hospital data with online datasets from reputable sources. This hybrid approach ensures a comprehensive representation of anemia cases, combining the specificity of locally sourced, manually labeled data with the broader scope offered by online datasets. By incorporating these diverse elements, our dataset will enable the development of a machine learning model that not only excels in local healthcare contexts but also exhibits broader applicability across various demographics and scenarios.

V. CONCLUSION

In conclusion, our anemia detection system is enriched by insights drawn from an extensive literature survey. The emphasis on local dataset curation from nearby hospitals, guided by the knowledge gleaned from various research papers, forms a cornerstone of our approach. The literature survey highlights the global burden of anemia and underscores the need for accessible point-of-care screening.

Our project's strength lies in the amalgamation of these insights into a cohesive framework, with a distinct focus on the locally curated dataset from hospitals. As we progress, the lessons drawn from the literature survey and the comparative analysis of various methodologies will guide the development of a robust anemia detection model. By incorporating elements from machine learning algorithms, ensemble learning techniques, and image processing with CNN, our approach aims to provide a comprehensive and accurate diagnostic solution. This fusion of methodologies reflects the evolving landscape of anemia detection, showcasing the potential for future research to integrate diverse approaches for a holistic diagnostic framework tailored to specific healthcare contexts.

REFERENCES

[1] Parab, M.A., Mehendale, N.D. Red Blood Cell Classification Using Image Processing and CNN. SN COMPUT. SCI. 2, 70 (2021). https://doi.org/10.1007/s42979-021-00458-2.

[2] P. T. Dalvi and N. Vernekar, "Anemia detection using ensemble learning techniques and statistical models," 2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), Bangalore, India, 2016, pp. 1747-1751, doi: 10.1109/RTEICT.2016.7808133.

[3] S B. Sen, A. Ganesh, A. Bhan, S. Dixit and A. Goyal, "Machine learning based Diagnosis and Classification Of Sickle Cell Anemia in Human RBC," 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), Tirunelveli, India, 2021, pp. 753-758, doi: 10.1109/ICICV50876.2021.9388610.

[4] Jaiswal, M., Srivastava, A., Siddiqui, T.J. (2019). Machine Learning Algorithms for Anemia Disease Prediction. In: Khare, A., Tiwary, U., Sethi, I., Singh, N. (eds) Recent Trends in Communication, Computing, and Electronics. Lecture Notes in Electrical Engineering, vol 524. Springer, Singapore. https://doi.org/10.1007/978-981-13-2685-1_44.

[5] An R, Huang Y, Man Y, Valentine RW, Kucukal E, Goreke U, Sekyonda Z, Piccone C, Owusu-Ansah A, Ahuja S, Little JA, Gurkan UA. Emerging point-of-care technologies for anemia detection. Lab Chip. 2021 May 18;21(10):1843-1865. doi: 10.1039/d0lc01235a. PMID: 33881041; PMCID: PMC8875318.

[6] R. V. Pellegrino, A. C. Tarrobago and D. L. B. Zulueta, "Development of Anemia Cells Recognition System Using Raspberry Pi," 2023 15th International Conference on Computer and Automation Engineering (ICCAE), Sydney, Australia, 2023, pp. 198-203, doi: 10.1109/ICCAE56788.2023.10111486.

[7] Shahzad, Muhammad, Arif Iqbal Umar, Syed Hamad Shirazi, Zakir Khan, Asfandyar Khan, Muhammad Assam, Abdullah Mohamed, and El-Awady Attia. 2022. "Identification of Anemia and Its Severity Level in a Peripheral Blood Smear Using 3-Tier Deep Neural Network" Applied Sciences 12, no. 10: 5030. https://doi.org/10.3390/app1210503.

[8] Rizal, A.S. et al. (2022) 'Detecting anemia based on palm images using convolutional neural network', International Journal of Advanced Engineering Research and Science, 9(9), pp. 280–287. doi:10.22161/ijaers.99.29.

[9] Zhang A, Lou J, Pan Z, Luo J, Zhang X, Zhang H, Li J, Wang L, Cui X, Ji B, Chen L. Prediction of anemia using facial images and deep learning technology in the emergency department. Front Public Health. 2022 Nov 9;10:964385. doi: 10.3389/fpubh.2022.964385. PMID: 36438300; PMCID: PMC9682145.

[10] Nithya, R & Nirmala, K. (2022). Detection of Anaemia using Image Processing Techniques from microscopy blood smear images. Journal of Physics: Conference Series. 2318. 012043. 10.1088/1742-6596/2318/1/012043..

[11] A. Kovačević, A. Lakota, L. Kuka, E. Bečić, A. Smajović and L. G. Pokvić, "Application of Artificial Intelligence in Diagnosis and Classification of Anemia," 2022 11th Mediterranean Conference on Embedded Computing (MECO), Budva, Montenegro, 2022, pp. 1-4, doi: 10.1109/MECO55406.2022.9797180.

[12] S. C, A. M. R, D. M. D and D. M, "Curability Prediction Model for Anemia Using Machine Learning," 2022 8th International Conference on Smart Structures and Systems (ICSSS), Chennai, India, 2022, pp. 1-7, doi: 10.1109/ICSSS54381.2022.9782233.

[13] Mohammed A. Faris, Fadheelah S. Azeez, and Estabraq A. Hameed, "Estimation of Some Blood Parameters in Anemic Children Patients", Tikrit J. Pharm. Sci., vol. 16, no. 1, pp. 39–49, Dec. 2022.

[14] N. B. Noor, M. S. Anwar and M. Dey, "Comparative Study Between Decision Tree, SVM and KNN to Predict Anaemic Condition," 2019 IEEE International Conference on Biomedical Engineering, Computer and Information Technology for Health (BECITHCON), Dhaka, Bangladesh, 2019, pp. 24-28, doi: 10.1109/BECITHCON48839.2019.9063188.

[15] M. S. MOHAMMED, A. A. AHMAD and M. SARI, "Analysis of Anemia Using Data Mining Techniques with Risk Factors Specification," 2020 International Conference for Emerging Technology (INCET), Belgaum, India, 2020, pp. 1-5, doi: 10.1109/INCET49848.2020.9154063.

[16] S. J. Mohammed MOHAMMED, A. A. Ahmed, A. A. Ahmad and M. Sami MOHAMMED, "Anemia Prediction Based on Rule Classification," 2020 13th International Conference on Developments in eSystems Engineering (DeSE), Liverpool, United Kingdom, 2020, pp. 427-431, doi: 10.1109/DeSE51703.2020.9450234.

[17] Dhakal, Prakriti & Khanal, Santosh & Bista, Rabindra. (2023). Prediction of Anemia using Machine Learning Algorithms. International Journal of Computer Science and Information Technology. 15. 15-30. 10.5121/ijcsit.2023.15102.

[18] Bouwman AC, Hulsegge I, Hawken RJ, Henshall JM, Veerkamp RF, Schokker D, Kamphuis C. Classifying aneuploidy in genotype intensity data using deep learning. J Anim Breed Genet. 2023 May;140(3):304-315. doi: 10.1111/jbg.12760. Epub 2023 Feb 21. PMID: 36806175.

[19] M. Hasan, M. S. Tahosin, A. Farjana, M. A. Sheakh and M. M. Hasan, "A Harmful Disorder: Predictive and Comparative Analysis for fetal Anemia Disease by Using Different Machine Learning Approaches," 2023 11th International Symposium on Digital Forensics and Security (ISDFS), Chattanooga, TN, USA, 2023, pp. 1-6, doi: 10.1109/ISDFS58141.2023.10131838.

[20] Saputra DCE, Sunat K, Ratnaningsih T. A New Artificial Intelligence Approach Using Extreme Learning Machine as the Potentially Effective Model to Predict and Analyze the Diagnosis of Anemia. Healthcare (Basel). 2023 Feb 26;11(5):697. doi: 10.3390/healthcare11050697. PMID: 36900702; PMCID: PMC10000789.

[21] M. S. MOHAMMED, A. A. AHMAD and M. SARI, "Analysis of Anemia Using Data Mining Techniques with Risk Factors Specification," 2020 International Conference for Emerging Technology (INCET), Belgaum, India, 2020, pp. 1-5, doi: 10.1109/INCET49848.2020.9154063.

[22] Tuba Karagül Yıldız, Nilüfer Yurtay, Birgül Öneç, Classifying Anemia Types Using Artificial Learning Methods, Engineering Science and Technology, an International Journal, Volume 24, Issue 1, 2021, Pages 50-70, ISSN 2215-0986, https://doi.org/10.1016/j.jestch.2020.12.003.

[23] Sasikala, N. & Banu, Gulmohamed & Babiker, Thgani & Rajpoot, Pushp. (2021). A Role of Data Mining Techniques to Predict Anemia Disease. International Journal of Computer Applications. 174. 16-20. 10.5120/ijca2021921090.

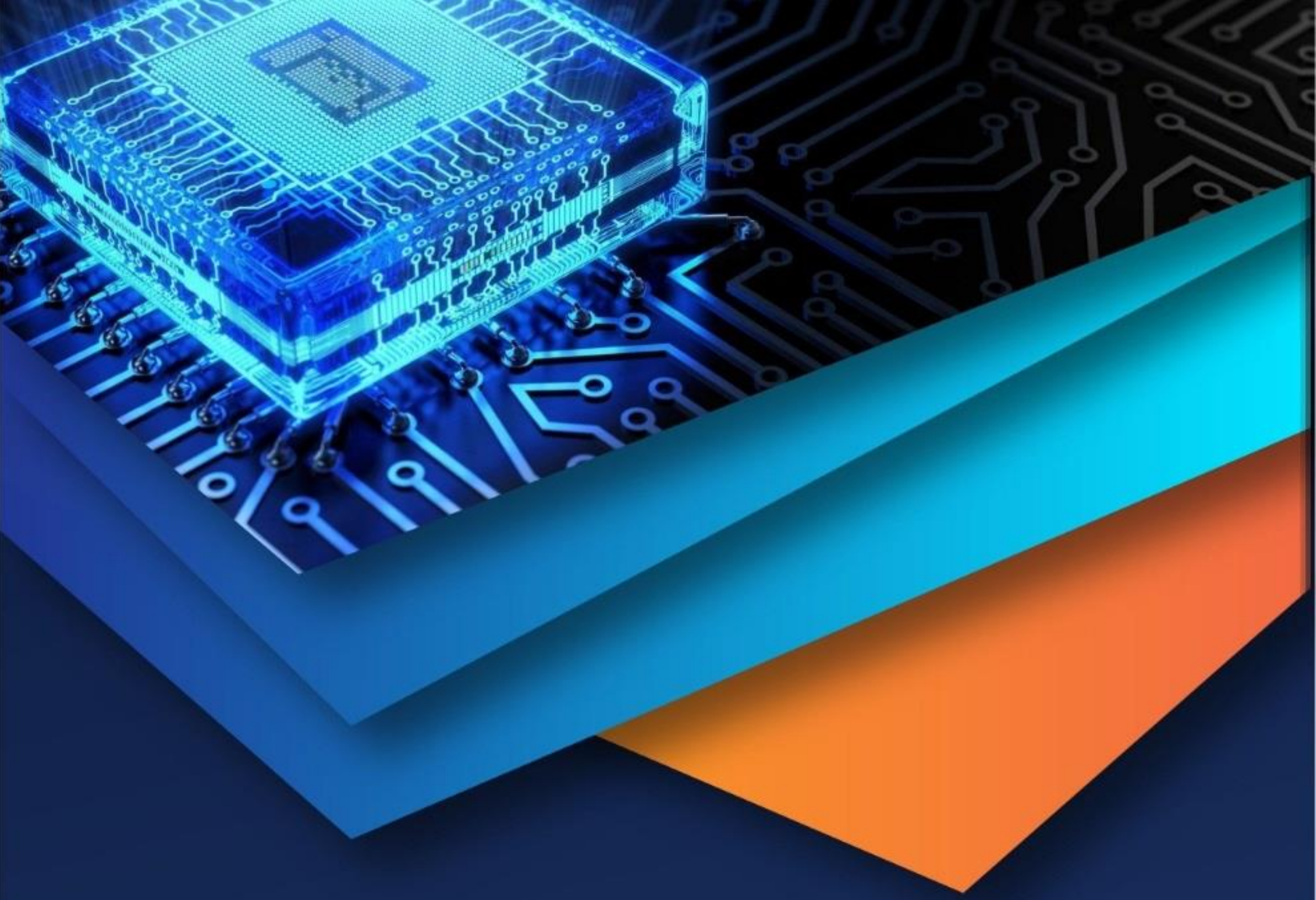
[24] Chakraborty, S., Kansara, K., Dinesh Kumar, R. et al. Non-invasive Estimation of Clinical Severity of Anemia Using Hierarchical Ensemble Classifiers. J. Med. Biol. Eng. 42, 828–838 (2022). https://doi.org/10.1007/s40846-022-00750-3

[25] Alzubaidi, Laith, Mohammed A. Fadhel, Omran Al-Shamma, Jinglan Zhang, and Ye Duan. 2020. "Deep Learning Models for Classification of Red Blood Cells in Microscopy Images to Aid in Sickle Cell Anemia Diagnosis" Electronics 9, no. 3: 427. https://doi.org/10.3390/electronics9030427

[26] Justice Williams Asare, PETER APPIAHENE, Emmanuel Timmy Donkoh, et al. Iron Deficiency Anemia Detection using Machine Learning Models: A Comparative Study of Fingernails, Palm and Conjunctiva of the Eye Images. Authorea. February 06, 2023. DOI: 10.22541/au.167570558.82410707/v1

[27] Vohra R, Hussain A, Dudyala AK, Pahareeya J, Khan W (2022) Multi-class classification algorithms for the diagnosis of anemia in an outpatient clinical setting. PLoS ONE 17(7): e0269685. https://doi.org/10.1371/journal.pone.0269685

[28] Memmolo, P. & Bianco, Vittorio & Russo, Roberta & Andolfo, Immacolata & Mugnano, Martina & Merola, Francesco & Miccio, Lisa & Iolascon, Achille & Ferraro, Pietro. (2023). Hierarchical learning approaches for improving label-free single-cell classification in holographic microscopy. 31. 10.1117/12.2674836.



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