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Survey on Different Techniques of Prediction of Transparent Anaemia using Artificial Intelligence

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Abstract: Anaemia is an endemic health disorder that is marked by low levels of haemoglobin or the count of red blood cells in the body, which causes serious health problems once it is not treated at the initial stages. The current anaemia diagnosis techniques are mostly based on statistical models and clinical risk scores which besides not being predictive; do not produce meaningful information to the medical practitioners. There are many authors studied in this paper are performing anaemia prediction using different machine learning technique and advance machine learning techniques. Many publicly available datasets and hospital datasets are used for performing this type of experiments which contributes to the study of anaemia prediction. Many researchers identified different limitations and improved their work to achieve the goal and even there is explainability of the model discussed by few authors for anaemia prediction. Authors detailed study and limitation with future scopes are mentioned in the paper for further opportunities of study on anaemia prediction.

Keywords: Anaemia prediction, machine learning, explainable artificial intelligence, healthcare analytics.

I. INTRODUCTION

Anaemia is one of the most widespread health disorders on the planet where the level of hemoglobin in blood or the number of red blood cells is decreased consequently impacting the oxygen-carrying capacity of blood and causing terribly dangerous health issues in case it is not detected in time. The World Health Organization claims that anaemia inflicts a huge percentage of the world population, especially women, children and those found in the developing regions. This thus necessitates early diagnosis and appropriate clinical management to avert fatigue, impaired thinking and dysfunction of organs. Nonetheless, traditional methods of diagnosis are primarily based on laboratory blood tests and statistical risk assessment procedures that lack a predictive potential and fail to present adequate information about the causes of the disease.

As the domain of artificial intelligence and data-driven healthcare analytics rapidly evolves, machine learning methods have become a potent instrument of disease prediction and clinical decision support. Many machine learning models including Support Vector Machines (SVM), Decision Trees, K-Nearest Neighbors (KNN), and ensemble learning algorithms have been extensively applied in the prediction of medical disorders like anaemia using clinical and hematological variables. The models are capable of identifying intricate trends in patient data and making precise predictions that are useful in helping healthcare workers in early diagnosis and treatment planning [1], [5]. Nevertheless, even with their predictive functions, numerous machine learning models act as black-box systems, so that clinicians cannot see the rationale behind predictions, and thus many of them cannot be implemented in the healthcare setting in practice.

To solve this problem, Explainable Artificial Intelligence (XAI) has been proposed to enhance transparency and interpretability in machine learning-based medical systems. SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are XAI methods that enable a researcher or clinician to understand the effect of varying features in inputs on the model predictions. These methods can give more than just useful explanations of individual predictions, which enhances trust and reliability in AI-assisted healthcare applications [3], [4]. Explainable models can help healthcare professionals to comprehend the diagnostic results better and make rational medical decisions because of highlighting the role of key clinical

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characteristics, including hemoglobin levels, red blood cell count, and other hematological indicators.

Recent research has established that integration of machine learning models and explainability methods largely improves the performance of disease prediction systems. As an illustration, a number of researchers have proposed explainable models of anaemia prediction with the ensemble learning and feature importance analysis to determine the main medical indicators of anaemia diagnosis [2], [6]. These methods do not only enhance the accuracy of prediction but also offer the clinically interpretable insight to aid in the decision-making procedures. Combining explainable AI with predictive models is thus a significant contribution to intelligent healthcare systems, as it allows a high level of predictive quality and clear decision support.

Inspired by these developments, this paper introduces an anaemia prediction framework that is transparent and utilizes several machine learning algorithms with explainable artificial intelligence techniques. The model proposed makes use of classifiers, including SVM, Decision Trees, KNN, and Gradient Boosting to forecast anaemia conditions with the help of clinical datasets. Moreover, explainability methods like SHAP and LIME are also added to examine and illustrate the impact of features on the prediction. The proposed system will help fill the gap between machine learning models and their application in a hospital environment and ultimately aid healthcare professionals in the early detection and management of anaemia by integrating predictive accuracy and interpretability.

II. LITERATURE SURVEY

A transparent anaemia prediction framework, which is capable of Explainable Artificial Intelligence (XAI), was suggested by Farooq et al. to address the black-box restrictions of conventional machine learning models in the healthcare industry [1]. Several classifiers were applied in the study to enhance clinical interpretability: SVM, Decision Trees, KNN, and Gradient Boosting are used alongside SHAP and LIME explainability methods. Their model was found to be highly predictive with feature level explanation hence increasing the confidence of the clinicians. The article has stressed the need to be transparent about AI-based medical diagnosis and how explainable models can help reduce the gap between predictive accuracy and clinical practice.

Bhowmik and Nasir tested an adaptive anemia diagnosis framework with tree-based machine learning models with XAI methods on actual clinical data in one of the hospitals in Bangladesh [2]. The experiment used the Random Forest, Gradient Boosting, and Extra Trees classifiers with intense data pre-processing, statistical validation, and hyperparameter optimization. The largest influential feature in the diagnosis of anemia was identified to be hemoglobin level as identified by SHAP-based explanations. Their framework proved to be highly generalized and emphasized on explainable decision support systems to a clinical setting.

Darshan et al. devoted their attention to the interpretable machine learning and explainable AI methods of the differential diagnosis between iron deficiency anemia and aplastic anemia [3]. The experiment involved blood test features gathered in one of the medical organizations and implementing several XAI methods such as SHAP, LIME, ELI5, and Anchor. The study gave profound insights on the feature significance and decision rationale, which enables the clinicians to comprehend and trust the model results. This study demonstrated that XAI is effective in the development of a complex diagnostic decision in hematological disorders.

The paper by Agrawal et al. examined the concept of explainable AI integration with machine learning to improve the accuracy of disease prediction and decision transparency in various medical conditions, such as anemia [4]. The recommended hybrid model was a combination of the Decision Trees, Naive Bayes, Random Forest, and XGBoost with the SHAP and LIME elucidations. Their outcomes were highly accurate and better interpretable and addressed the trust gap that is closely linked with AI systems in the medical field. The paper supported the importance of XAI in allowing clinician-friendly AI-based diagnosis systems.

BS et al. proposed an ensemble machine learning model that is coupled with explainable artificial intelligence to identify haemoglobin-based

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anaemia through the use of hematological biomarkers [5]. It was done by training several classifiers and ensembling them through a stacking strategy to reach accuracy, precision and recall values of 99%. Model predictions were interpreted using XAI techniques and clinical significant blood markers were determined. The study highlighted the efforts of ensemble learning integrated with explainability in enhancing the results of early diagnosis and treatment.

Ref. No.	Author(s)	Title / Focus	Methods / Models Used	XAI Techniques	Key Findings
[1]	Farooq et al.	Transparent anemia prediction framework	SVM, Decision Tree, KNN, Gradient Boosting	SHAP, LIME	Proposed an explainable anemia prediction system to overcome black-box limitations in healthcare. The framework achieved high predictive performance and provided feature-level explanations, improving clinician trust and interpretability.
[2]	Bhowmik and Nasir	Adaptive anemia diagnosis framework using clinical data	Random Forest, Gradient Boosting, Extra Trees	SHAP	Developed a tree-based anemia diagnosis model using real hospital data from Bangladesh. Hemoglobin was identified as the most influential feature, and the framework showed strong generalization ability in clinical settings.
[3]	Darshan et al.	Differential diagnosis of iron deficiency anemia and aplastic anemia	Interpretable machine learning models on blood test features	SHAP, LIME, ELI5, Anchor	Focused on distinguishing between two hematological disorders using explainable ML. The study provided strong insights into feature importance and helped clinicians understand model decisions better.
[4]	Agrawal et al.	Explainable AI integration for disease prediction including anemia	Decision Tree, Naive Bayes, Random Forest, XGBoost	SHAP, LIME	Proposed a hybrid explainable AI framework for accurate and transparent disease prediction. The model improved both prediction accuracy and interpretability, helping bridge the trust gap in medical AI systems.
[5]	BS et al.	Ensemble learning for hemoglobin-based anemia	Ensemble learning with stacking strategy	XAI-based interpretation	Presented a stacking-based ensemble model for anemia detection using hematological biomarkers. The model achieved around 99%

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		detection			accuracy, precision, and recall, while also identifying clinically significant blood markers.
[6]	Kasthuri et al.	Explainable anemia prediction among young population	LightGBM and other machine learning models	XAI analysis	Developed an anemia prediction system after preprocessing and balancing the dataset. LightGBM performed best, and explainability analysis highlighted major contributing factors useful for clinical judgment.
[7]	Darshan et al.	Machine learning-based anemia detection system	Random Forest, KNN, SVM, XGBoost	SHAP, LIME, QLattice, ELI5	Compared multiple classifiers for automated anemia diagnosis and achieved accuracy up to 98%. Explainability tools helped identify influential features and improved reliability of decision support systems.
[8]	Zemariam et al.	Prediction and classification of anemia in adolescent girls in Ethiopia	Random Forest, Logistic Regression, Decision Tree	Not specifically mentioned	Applied supervised machine learning on clinical and demographic data to predict anemia. Data preprocessing, feature selection, and normalization improved performance, showing the value of ML in early anemia detection and risk identification.
[9]	Muriithi et al.	Explainable AI for malaria risk prediction	Multiple machine learning algorithms	Explainability tools	Developed an XAI-supported malaria risk prediction model using epidemiological and environmental data. The model improved transparency and helped medical professionals understand the major risk factors influencing predictions.
[10]	Awe et al.	Explainable ensemble machine learning for malaria diagnosis	Classification models with ensemble learning	Explainability techniques	Proposed an ensemble-based explainable system for malaria diagnosis. The approach improved predictive accuracy and clearly identified the important clinical attributes affecting diagnostic decisions.

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A prediction system of anemia was suggested by Kasthuri et al., which combines explainable artificial intelligence as a predictor to understand the underlying causes of anemia among the young population [6]. The research implied preprocessing of data, removing class imbalance, and deploying various machine learning models. Light Gradient Boosting model was more accurate and the XAI analysis resulted in the prevalent contributing attributes that impacted on anemia prediction. This practice helped healthcare workers make quality and clear clinical judgments.

Darshan et al. created an anemia detection machine-learning-based system on the basis of clinical markers and various explainable AI methods [7]. The study compared various classifiers such as Random Forest, KNN, SVM and XGBoost with a high accuracy rate of up to 98. Predictions and influential features were explained using explainability tools like SHAP, LIME, QLattice and ELI5. The paper has proved that it is possible to implement explainable AI-based decision support systems to achieve correct and automated anemia diagnosis.

Zemariam et al. suggested a machine learning-assisted method to categorize and forecast anaemia in adolescent girls within Ethiopia utilizing clinical and demographic health data that is supervised [8]. The research used a number of different classification algorithms such as the random forests, Logistic regression and decision trees to determine patterns correlated to the prevalence of anaemia. Normalization, feature selection, and missing values are some of the data preprocessing techniques that were used to enhance predictive performance of the models. The findings of the experiment indicated that the machine learning models were able to predict the cases of anaemia successfully with high predictivity, which indicated the significance of data-driven methods in the early diagnosis of anaemia within the healthcare systems. Another point of the study was that machine learning-based prediction models can help healthcare professionals to detect high-risk groups and enhance preventive healthcare measures.

Muriithi et al. have created an explainable artificial intelligence (XAI) system, a malaria risk prediction model in Kenya based on machine learning algorithms and explainability tools [9]. The objective in the study was to enhance the predictive models applied in healthcare decision support systems with respect to transparency and interpretability. Different machine learning models were used to investigate the epidemiological and environmental data related to the transmission of malaria. The combination of XAI techniques made it possible to reveal significant risk factors related to malaria prediction, and give explanatory results to medical professionals. The study has shown that explainable AI models may contribute to substantial increases in trust in AI-based healthcare systems because clinicians can determine the rationale behind model predictions.

Awe et al. also suggested an explainable machine learning model-based system to improve the precision of malaria diagnosis [10]. The experiment used various methods of classification and fused them with ensemble learning methods to enhance predictive accuracy. To address the shortcoming of the black-box models, explainability techniques were included to emphasize the most important clinical attributes that influenced diagnostic decision-making. The findings demonstrated that the combination of ensemble learning and explainable AI was much more beneficial in regards to diagnosing instances and offering clear explanations of the predictions. This paper has emphasized the opportunities of explainable AI systems in helping to have reliable and interpretable medical diagnostic systems.

III. CHALLENGES AND GAP IN THE RESEARCH.

Although there have been major advancements in the implementation of machine learning and explainable artificial intelligence in the field of medical diagnosis, there are a number of challenges and research gaps in the creation of effective anaemia prediction systems.

A significant problem is the shortage of good quality medical datasets. Numerous current studies are based on small, or region-specific data which can restrict the predictive models to be applicable to other population and health care settings. There are also no standardized datasets and therefore comparing the performance of various prediction models is not easy.

The other difficulty is that machine learning models are not easily interpretable. Though explainable AI methods like SHAP and

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LIME have been developed to enhance transparency, the complexity of relationships between clinical characteristics and prediction results is still not easily comprehended by non-technical healthcare experts. This has the potential to influence the implementation of AI-based diagnostic systems in actual clinical practice.

Also, most of the existing models pay more attention to prediction accuracy and neglect clinical usability. Although high accuracy is also essential, healthcare workers must have interpretable explanations that ensure that the impact of each clinical parameter on the prediction outcomes is clear.

The other gap in research is that it has not been integrated with real-time healthcare systems. Majority of the available research studies emphasize on experimental studies based on offline datasets instead of designing deployable clinical decision support systems. This restricts the application of AI models in healthcare facilities and hospitals.

Lastly, medical AI systems prejudice and equality is a significant issue. Modeled machine learning systems that are trained using unbalanced data can be predicted with bias, which can apply to specific groups of individuals. The future research on this topic is thus of urgent need to address the issue of fairness and ethical concerns regarding AI-based healthcare applications.

IV. FUTURE RESEARCH DIRECTIONS

To improve the quality and trustworthiness of the healthcare decision support system and make it more efficient, future studies in the field of anaemia forecasting with the help of machine learning and explainable artificial intelligence can center their attention on several valuable directions.

To begin with, the researchers need to concentrate on the creation of large-scale and varied medical data that contains clinical records of various groups of people and geographical areas. This will assist in enhancing the generalization power of predictive models and allow to detect anaemia more accurately in a variety of healthcare settings.

Second, more studies are required to enhance the interpretability of machine learning models. Explainable AI methods can be advanced to create more visual explanations and an analysis of the features that are easy to understand by healthcare professionals.

One more valuable direction is the combination of machine learning models and real-time healthcare systems and electronic health records (EHR). This kind of integration will enable predictive models to evaluate continuous patient data and give real-time decision support to the clinicians.

Researchers can also consider the hybrid and ensemble machine learning where several algorithms are combined to enhance predictive accuracy and strength. It is possible to further improve the work of anaemia prediction systems by combining traditional machine learning with deep learning techniques.

Lastly, further research and practice in the future should revolve around ethical aspects, fairness, and bias in AI-based healthcare models. Creating transparent and trustworthy artificial intelligence systems that would adhere to ethical standards will aid in the higher acceptance of artificial intelligence in clinical settings.

V. CONCLUSION

The paper demonstrates different prediction system used for anaemia using machine learning and deep learning techniques. In addition to the machine learning and deep learning there are different enhancements are done such as explainable AI and additional patient care tolls are used by different researchers. Many authors did comprehensive study on clinical data obtained for anaemia from different resources. Many researchers used the high performing algorithm without integration of innovation things like explainable AI and disease control using patient care. So, future work is to add advance machine learning or deep learning algorithms with more patient care techniques so that patient will prefer to use this application instead of other available applications.

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