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# CLASSIFICATION AND PREDICTION OF SEVERITY OF INFLAMMATORY BOWEL DISEASE USING MACHINE LEARNING

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## ABSTRACT

This study presents a machine learning-based approach for classifying and predicting the severity of Inflammatory Bowel Disease (IBD) in children and adolescents using vitamin D levels. IBD is a chronic inflammatory condition of the gastrointestinal tract, with evidence linking low vitamin D levels to increased disease risk and complications, including colon cancer. Early intervention with adequate vitamin D levels may play a protective role in gut health, making predictive analysis crucial for timely diagnosis and treatment. This research utilizes an open dataset comprising serum 25(OH)D concentrations and other clinical features of patients aged 2 to 20 years. The severity of IBD is categorized into three classes—low risk, moderate risk, and high risk. Various machine learning models, including Decision Trees, Support Vector Machines (SVM), and Ensemble Boosted Trees, are employed to classify the disease severity. Comparative analysis reveals that the Ensemble Boosted Trees classifier achieves the highest accuracy of 98% with an area under the ROC curve (AUC) of 0.98. These findings demonstrate the potential of machine learning in enhancing early diagnosis and personalized treatment strategies for IBD patients.

## I.INTRODUCTION

Inflammatory Bowel Disease (IBD) is a chronic disorder characterized by persistent inflammation of the gastrointestinal (GI) tract, encompassing conditions such as Crohn's disease and ulcerative colitis. The prevalence of IBD has been rising globally, particularly among children and adolescents, necessitating early diagnosis and precise disease management to mitigate long-term complications. Emerging research suggests a strong correlation between vitamin D levels and IBD severity, with deficiencies often linked to increased disease risk, impaired immune response, and a higher likelihood of complications such as colorectal cancer. Given its immunomodulatory properties, vitamin D plays a crucial role in maintaining gut health, and its early monitoring can aid in risk assessment and treatment planning for IBD patients. The integration of machine learning in healthcare has revolutionized disease prediction and classification, offering automated, data-driven insights that enhance clinical decision-making. Traditional diagnostic methods for IBD rely on invasive procedures such as colonoscopy and biopsy, which can be uncomfortable and resource-intensive. Machine learning algorithms, on the other hand, provide a non-invasive alternative by leveraging clinical and biochemical data to predict disease severity with high accuracy. In this study, we utilize an open-access dataset containing serum 25(OH)D concentrations and other clinical features of pediatric patients (aged 2 to 20 years) diagnosed with IBD. The dataset is classified into three severity levels—low risk, moderate risk, and high risk—based on key biomarkers and

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clinical parameters. Various machine learning models, including Decision Trees, Support Vector Machines (SVM), and Ensemble Boosted Trees, are applied to classify IBD severity. A comparative analysis of these models is conducted to identify the most effective approach for predicting disease progression. The primary objective of this research is to develop an accurate and efficient machine learning model that can assist healthcare professionals in early diagnosis and personalized treatment planning for IBD patients. The findings of this study highlight the potential of machine learning in transforming gastroenterology by providing predictive insights that enable proactive disease management, ultimately improving patient outcomes.

## II.LITERATURE REVIEW

The increasing global prevalence of Inflammatory Bowel Disease (IBD), particularly among children and adolescents, has necessitated the exploration of novel diagnostic and predictive approaches. Traditional methods of diagnosing IBD, such as colonoscopy and histopathological examinations, are invasive and may not be suitable for early-stage detection. As a result, recent research has focused on leveraging machine learning (ML) techniques to improve the accuracy and efficiency of IBD severity classification and prediction.

### Role of Vitamin D in IBD Progression

Several studies have highlighted the relationship between vitamin D levels and IBD severity. Vitamin D, particularly serum 25(OH)D, is known for its immunomodulatory effects, which play a crucial role in gut health and inflammation regulation. Research by Cantorna et al. (2019) demonstrated that vitamin D deficiency is associated with an increased risk of IBD flare-ups and complications, including colon cancer. Another study by Li et al. (2021) provided evidence that sufficient vitamin D supplementation may reduce disease severity and improve gut microbiota composition in IBD patients. These findings suggest that vitamin D levels can serve as a potential biomarker for predicting disease severity and guiding treatment plans.

### Machine Learning in Disease Prediction

Machine learning has been widely applied in healthcare for disease classification, risk assessment, and personalized treatment recommendations. In recent years, ML models have shown promising results in predicting various chronic conditions, including diabetes, cardiovascular diseases, and cancer. In the context of IBD, ML techniques have been employed to analyze clinical and biochemical data to predict disease onset, progression, and treatment response.

Studies have utilized Support Vector Machines (SVM), Decision Trees, Random Forest, and ensemble learning models to enhance the accuracy of IBD classification. According to a study by Lee et al. (2020), SVM and Random Forest models achieved high accuracy in distinguishing between Crohn’s disease and ulcerative colitis based on patient data, demonstrating the potential of ML-based approaches in IBD diagnosis. Similarly, Rahman et al. (2022) proposed an ensemble learning method that combined boosted trees and deep learning models, achieving an accuracy of over 95% in predicting IBD severity.

**Challenges in Machine Learning-Based IBD Classification**

Despite its advantages, ML-based IBD classification faces several challenges. One major issue is data imbalance, where the number of high-risk patients is significantly lower than those at moderate or low risk. This can lead to biased predictions, where ML models fail to accurately identify severe cases. Researchers have addressed this problem using data augmentation, synthetic oversampling (SMOTE), and feature selection techniques to enhance model performance.

Another challenge is the interpretability of ML models in clinical settings. Deep learning models, such as Convolutional Neural Networks (CNNs), often provide high accuracy but lack transparency, making it difficult for medical professionals to trust automated predictions. Efforts are being made to develop explainable AI (XAI) techniques to improve the interpretability of ML models in healthcare applications.

**Recent Advances and Future Directions**

Recent advancements in ensemble learning and hybrid models have significantly improved disease classification performance. Studies have demonstrated that combining multiple classifiers, such as Decision Trees, SVM, and Neural Networks, enhances robustness and reduces bias in IBD severity classification. The integration of clinical, genetic, and biochemical markers is also being explored to improve predictive accuracy. Future research aims to incorporate real-time patient monitoring using wearable devices and electronic health records (EHRs) to provide continuous risk assessment for IBD patients. Additionally, integrating multi-omics data, such as gut microbiome analysis and genetic profiling, could further refine the predictive models and enable personalized treatment recommendations.

## III.WORKING METHODOLOGY

The classification and prediction of Inflammatory Bowel Disease (IBD) severity using machine learning follow a structured methodology to ensure accurate and reliable results. The process begins with data collection, where clinical records of pediatric patients aged 2 to 20 years diagnosed with IBD are gathered. The dataset includes 31 features such as demographic details (age, gender, BMI), clinical attributes (disease history, severity index), and biochemical parameters like Serum 25(OH)D (Vitamin D) concentration, CRP (C-reactive protein), and hemoglobin levels. Patients are categorized into three severity classes: low risk, moderate risk, and high risk.

To improve data quality, preprocessing techniques are applied, including handling missing values using the K-Nearest Neighbors (KNN) imputation method, normalizing continuous features with Min-Max Scaling, and detecting outliers using the Z-score and IQR (Interquartile Range) method. Since the dataset is imbalanced, Synthetic Minority Oversampling Technique (SMOTE) is used to balance the class distribution. Feature selection is then performed using the Recursive Feature Elimination (RFE) technique, ensuring that only the most relevant attributes—such as vitamin D levels, CRP, hemoglobin, and BMI—are used for classification.

For model selection, multiple machine learning classifiers are implemented and compared. A Decision Tree Classifier is first used for its interpretability, followed by Support Vector Machine (SVM) with the Radial Basis Function (RBF) kernel, which helps in handling complex non-linear classification. Additionally, ensemble learning techniques like XGBoost and Random Forest are deployed to improve classification performance. The dataset is split into a 70-30 training-testing ratio, and 5-fold cross-validation is applied to minimize overfitting. To evaluate model performance, several metrics are used, including accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic (ROC) Curve (AUC-ROC). The Ensemble Boosted Tree Classifier achieves the highest classification accuracy of 98%, indicating its superior predictive capability. This trained model is then deployed as a decision support system to assist medical professionals in early diagnosis and personalized treatment planning. Given a patient's clinical attributes, the system predicts the IBD severity level and provides insights for proactive medical intervention. The final step involves deployment and future enhancements. The model is integrated into a web-based or mobile application for real-time accessibility. Further improvements include incorporating deep learning techniques (CNN, LSTM), integrating real-time monitoring with wearable sensors, and utilizing multi-omics data fusion, combining genetic, microbiome, and biochemical markers for more comprehensive disease prediction. This methodology demonstrates a structured and AI-driven approach to identifying IBD severity, with machine learning playing a crucial role in early detection, risk classification, and improved patient management.

## IV.CONCLUSION

The classification and prediction of Inflammatory Bowel Disease (IBD) severity using machine learning offer a significant advancement in early diagnosis and personalized treatment planning. This study effectively demonstrates how AI-driven predictive models can assist healthcare professionals in identifying high-risk pediatric patients based on clinical and biochemical parameters, particularly Serum 25(OH)D (Vitamin D) levels. The dataset, consisting of 31 features, was preprocessed to ensure data quality, and various classifiers—including Decision Trees, Support Vector Machines (SVM), and Ensemble Boosted Trees—were employed. Among these, the Ensemble Boosted Tree classifier achieved the highest accuracy of 98%, making it the most effective model for severity classification.

The results suggest that vitamin D deficiency plays a critical role in disease severity, reinforcing the need for early supplementation and monitoring in high-risk individuals. The study also highlights the potential of machine learning in healthcare, not only for accurate disease classification but also for developing AI-powered decision support systems that aid in treatment planning. Future work can focus on integrating deep learning techniques, real-time patient monitoring, and multi-omics data fusion to enhance predictive performance further. The findings contribute to advancing precision medicine in pediatric IBD management, making early intervention more accessible and efficient.

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