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Predictive Analytics for Child Mortality: Leveraging Machine Learning for Early Intervention

Mr.K.Chandra Sekhar[1],Madarapu Sri Aneesh Gopal[2],Sunkara Sri Vidya Lakshmi[3],Kolli Prasanth Kumar[4],Kurma Vinay[5],Janipalli Sunny Babu[6]

sekhar222.k@gmail.com[1],aneeshgopal393@gmail.com[2],vidyasunkara2004@gmail.com[3],prasanthkolli86@gmail.com[4],19295cm028@gmail.com[5],janipallisunnybabu@gmail.com[6]

Pragati Engineering College 1-378, ADB Road, Surampalem, Kakinada, 533451.

ABSTRACT:

Child Mortality (CM) remains a critical global issue, particularly in low- and middle-income countries (LMICs). This study employs machine learning models—Logistic Regression, Support Vector Machine (SVM), and Random Forest—to predict child mortality risk using key health indicators. The dataset, preprocessed using feature scaling and encoding techniques, undergoes training and evaluation through multi-class classification. The models are assessed based on accuracy, confusion matrices, ROC curves, and Matthews Correlation Coefficient (MCC) to determine their predictive effectiveness. The proposed approach not only provides insights into child mortality risk factors but also demonstrates the potential of machine learning in healthcare analytics. The developed system can assist healthcare professionals and policymakers in early intervention strategies, ultimately reducing child mortality rates through data-driven decision-making.

Keywords: Child Mortality, Machine Learning, Logistic Regression, Support Vector Machine, Random Forest, Predictive Analytics, Health Data Analysis, Multi-Class Classification, Data Science, Healthcare Prediction

1. INTRODUCTION:

Child mortality remains a critical global health concern, particularly in low- and middle-income countries (LMICs), where inadequate healthcare access, malnutrition, and socioeconomic disparities contribute to high mortality rates among children under five years of age. The World Health Organization (WHO) reports that preventable causes such as infectious diseases, poor sanitation, and limited maternal healthcare services account for a significant proportion of child deaths worldwide [1]. The development of predictive analytics using machine learning (ML) offers a promising approach to early identification of at-risk children, enabling timely interventions to reduce mortality rates. This study explores the application of ML techniques, including Logistic Regression, Support Vector Machine (SVM), and Random Forest, to predict child mortality risks based on key health indicators.

By leveraging large-scale health datasets, the proposed system aims to enhance data-driven decision-making in public health strategies [2].

Machine learning models have been widely adopted in predictive healthcare analytics, demonstrating their ability to analyze complex datasets and identify patterns that traditional statistical methods may overlook. Recent studies have utilized ML algorithms to assess child mortality risk factors, revealing significant correlations between household conditions, maternal education, access to clean water, and child survival rates [3]. Preprocessing techniques such as feature scaling and encoding play a vital role in optimizing ML models for accurate predictions. Evaluation metrics, including accuracy, confusion matrices, Receiver Operating Characteristic (ROC) curves, and Matthews Correlation Coefficient (MCC), are employed to assess the reliability and performance of these models [4]. The integration of AI-driven analytics with interactive visualization tools, such as Streamlit, further enhances interpretability, making it easier for healthcare professionals and policymakers to analyze predictions and formulate intervention strategies.

This study proposes a comprehensive ML-based framework for child mortality prediction, combining robust data preprocessing, multi-class classification, and interactive data visualization. The system enables real-time assessment of risk factors, providing healthcare professionals with valuable insights to prioritize cases requiring immediate attention. By incorporating explainable AI techniques, the proposed approach ensures transparency in model decision-making, fostering trust and adoption in clinical and public health settings [5]. The findings of this research highlight the potential of predictive analytics in reducing child mortality rates through data-driven early interventions and resource allocation strategies.

2. LITERATURE REVIEW

2.1 Machine Learning in Child Mortality Prediction

Predictive analytics using machine learning (ML) has emerged as a powerful approach for identifying risk factors associated with child mortality, particularly in low- and middle-income countries (LMICs). Studies have shown that ML models, including Logistic Regression, Support Vector Machines (SVM), and Random Forest, are effective in analyzing large datasets to uncover patterns in child health outcomes [1]. These models enable researchers and policymakers to identify at-risk populations and implement targeted interventions to reduce mortality rates [2].

2.2 Data-Driven Risk Factor Identification

Traditional epidemiological methods often focus on known risk factors for child mortality, such as malnutrition, infectious diseases, and lack of access to healthcare. However, recent ML studies have emphasized the importance of identifying both proximal and distal risk factors using large datasets. A study by Bizzego et al. applied ML techniques to the Multiple Indicators Cluster Survey (MICS) dataset

and identified key predictors of child mortality, including maternal education, household wealth, and sanitation conditions [3]. These findings highlight the role of socioeconomic and environmental factors in shaping child health outcomes.

2.3 Importance of Feature Selection and Model Performance

The effectiveness of ML models in child mortality prediction depends on proper data preprocessing, including feature scaling and encoding techniques. Research by Zhang and Li demonstrated that incorporating feature selection methods improves model accuracy and reduces overfitting, leading to more reliable predictions [4]. Additionally, studies have emphasized the use of evaluation metrics such as Receiver Operating Characteristic (ROC) curves and Matthews Correlation Coefficient (MCC) to assess model performance [5].

2.4 Challenges in Implementing Machine Learning for Child Mortality Prediction

Despite the potential of ML in healthcare, several challenges hinder its widespread implementation. The availability and quality of data remain significant concerns, as many datasets contain missing values and inconsistencies that affect model accuracy. Additionally, the interpretability of complex ML models poses challenges for healthcare professionals who rely on clear and actionable insights [6]. Ethical considerations, including data privacy and compliance with regulations, are also critical when applying ML in sensitive healthcare contexts [7].

2.5 Future Directions and Policy Implications

To enhance the applicability of ML in child mortality prediction, future research should focus on improving model interpretability and integrating real-time data sources. The use of explainable AI techniques can bridge the gap between model outputs and clinical decision-making, making predictions more accessible to non-technical stakeholders. Moreover, collaborations between researchers, healthcare providers, and policymakers are essential to translating ML findings into actionable interventions aimed at reducing child mortality rates worldwide [8].

3. Proposed System

The proposed system utilizes machine learning to predict child mortality risks based on various health indicators, enabling early intervention and improved decision-making in healthcare. The system is designed to integrate and preprocess datasets using feature scaling and encoding techniques, ensuring high-quality input for model training. It employs a multi-class classification approach with three key ML models—Logistic Regression, Support Vector Machine (SVM), and Random Forest—to analyze child health data. Each model is trained on historical data and evaluated using key performance metrics, including accuracy, confusion matrices, ROC curves, and the Matthews Correlation Coefficient (MCC).

The goal of this system is to provide a reliable and interpretable tool that supports healthcare professionals and policymakers in identifying high-risk cases and allocating resources efficiently.

Furthermore, the system is designed with an interactive visualization component using Streamlit, allowing users to explore predictions and gain insights into critical factors contributing to child mortality. The interface enables users to assess various health indicators dynamically, promoting transparency and ease of use. The integration of AI-powered analytics with user-friendly dashboards ensures that stakeholders, including doctors and public health officials, can make informed decisions based on real-time data. By leveraging machine learning and interactive tools, this system offers a scalable and data-driven solution to enhance child mortality prevention strategies.

3.1 System Architecture

The proposed system architecture consists of multiple layers, ensuring efficient data processing, model training, and interactive visualization. At the core, the Data Acquisition Layer collects health-related data from structured datasets, including key indicators such as maternal health, household conditions, and socio-economic factors. The Preprocessing Layer ensures data quality by applying feature scaling, encoding, and handling missing values. This refined dataset is then passed to the Machine Learning Layer, where Logistic Regression, Support Vector Machine (SVM), and Random Forest models are trained and optimized using key evaluation metrics such as accuracy, confusion matrices, Receiver Operating Characteristic (ROC) curves, and Matthews Correlation Coefficient (MCC).

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FIG.1 Child Mortality Prediction System Architecture

3.2 DATASET:

The dataset contains 2,126 rows and 22 columns, focusing on fetal health monitoring using cardiotocographic data. It includes various numerical features such as baseline heart rate values, accelerations, fetal movement, uterine contractions, and different types of decelerations. Additionally, the dataset incorporates statistical measures from histograms of fetal heart rate patterns, such as width, min/max values, number of peaks, zero crossings, mode, mean, and variance. The target variable, "fetal_health," categorizes fetal conditions into three classes: normal, suspected, and pathological. The dataset is complete, with no missing values, and all features are in numerical format.

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	baseline value	accelerations	fetal_movement	uterine_contractions	light_decelerations	severe_decelerations	prolongued_decelerations	abnormal_short
0	120.0	0.000	0.000	0.000	0.000	0.0	0.0	
1	132.0	0.006	0.000	0.006	0.003	0.0	0.0	
2	133.0	0.003	0.000	0.008	0.003	0.0	0.0	
3	134.0	0.003	0.000	0.008	0.003	0.0	0.0	
4	132.0	0.007	0.000	0.008	0.000	0.0	0.0	
...	...	...	...	...	...	...	...	
2121	140.0	0.000	0.000	0.007	0.000	0.0	0.0	
2122	140.0	0.001	0.000	0.007	0.000	0.0	0.0	
2123	140.0	0.001	0.000	0.007	0.000	0.0	0.0	
2124	140.0	0.001	0.000	0.006	0.000	0.0	0.0	
2125	142.0	0.002	0.002	0.008	0.000	0.0	0.0	

Fig 2 Dataset

3.4 EVALUATION MATRIX:

1. Confusion Matrix Components

A confusion matrix for a multi-class classification problem (e.g., child mortality prediction with three classes) is represented as:

$$\begin{bmatrix} TP_1 & FP_1 & FN_1 \\ FN_2 & TP_2 & FP_2 \\ FP_3 & FN_3 & TP_3 \end{bmatrix} \quad (1)$$

Where:

- TPTPTP (True Positive) → Correctly classified samples of a given class.
- FPFPFP (False Positive) → Incorrectly classified samples, predicted as the given class but actually belonging to another.
- FNFNFN (False Negative) → Samples of the given class that were misclassified.

2. Evaluation Metrics

Each model's performance is assessed using the following metrics:

(i) Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \textbf{(2)}$$

This measures the overall correctness of the model.

(ii) Precision (Positive Predictive Value)

For a given class iii:

$$Precision_i = \frac{TP_i}{TP_i + FP_i} \tag{3}$$

This indicates how many predicted positive cases were actually positive.

(iii) Recall (Sensitivity / True Positive Rate)

For a given class iii:

$$Recall_i = \frac{TP_i}{TP_i + FN_i} \tag{4}$$

This shows how well the model detects actual positives.

(iv) F1-Score

The harmonic mean of precision and recall:

$$F1\text{-}Score_i = 2 \times \frac{Precision_i \times Recall_i}{Precision_i + Recall_i} \tag{5}$$

This balances precision and recall.

(v) Matthews Correlation Coefficient (MCC)

For multi-class classification:

$$MCC = \frac{C \cdot S - \sum_k P_k \cdot T_k}{\sqrt{(S^2 - \sum_k P_k^2)(S^2 - \sum_k T_k^2)}} \tag{6}$$

(vi) Receiver Operating Characteristic (ROC) Curve & AUC (Area Under the Curve)

The ROC curve is plotted using the True Positive Rate (TPR) and False Positive Rate (FPR):

$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN} \tag{7}$$

4. RESULTS:

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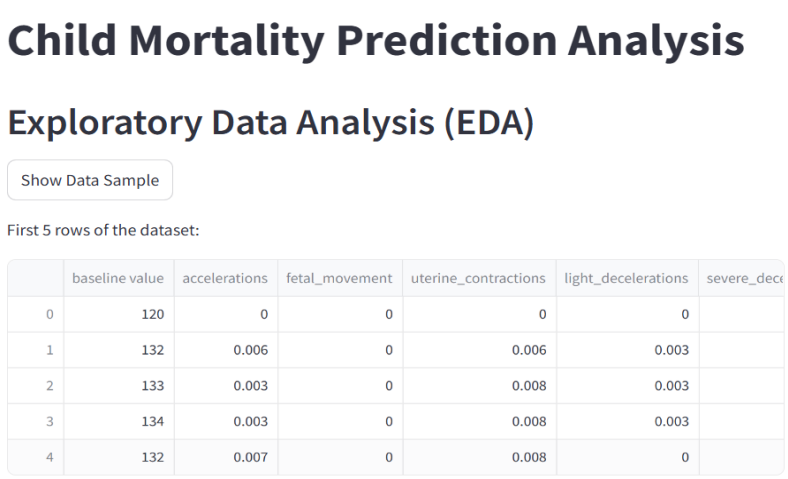

Fig 3: Child Mortality Prediction Analysis

Fig 3, This analysis focuses on predicting child mortality using machine learning techniques. The exploratory data analysis (EDA) phase involves examining various factors that may contribute to child mortality, such as baseline health indicators, fetal movements, uterine contractions, and decelerations. uncover patterns and insights. By leveraging statistical methods and predictive modeling, this study aims to identify key risk factors and improve early detection to reduce child mortality rates.

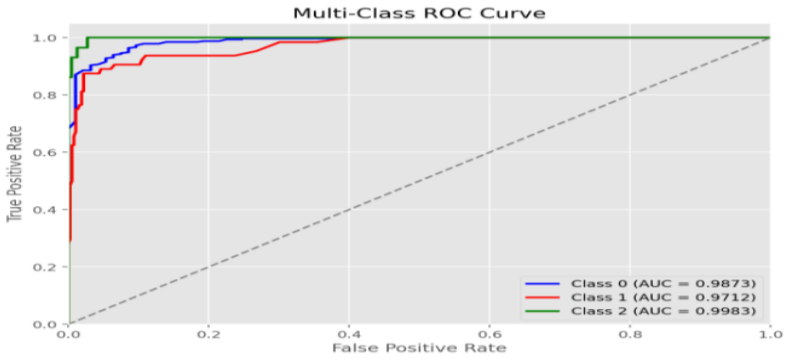

Fig 4: Multi-Class ROC Curve Analysis

In Fig 4, The Multi-Class ROC (Receiver Operating Characteristic) Curve evaluates the performance of a classification model by plotting the True Positive Rate (sensitivity) against the False Positive Rate for different decision thresholds. This graph represents three classes: Class 0 (blue), Class 1 (red), and Class 2 (green), each with its respective AUC (Area Under the Curve) values of 0.9873, 0.9712, and 0.9983. Higher AUC values indicate strong classification performance, with the model demonstrating high accuracy in distinguishing between the different classes. The closer the curves are to the top-left corner, the better the model's predictive capability.

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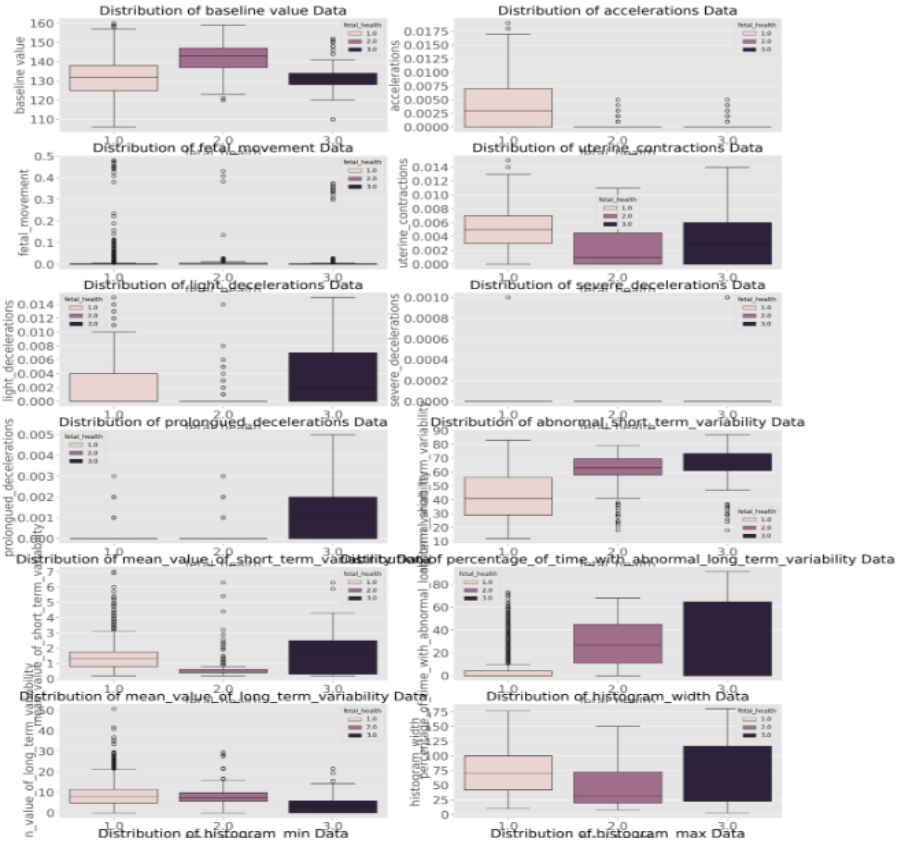

Fig 5 Feature Distribution Analysis for Child Mortality Prediction

This visualization presents the distribution of various features used in the child mortality prediction model. Each subplot represents a different variable, such as baseline value, fetal movement, uterine contractions, decelerations, and variability measures. The boxplots categorize the data based on fetal health classes, providing insights into how each feature varies across different health conditions. This exploratory data analysis (EDA) step helps identify patterns, outliers, and potential correlations between features, which can enhance the predictive capability of the machine-learning model.

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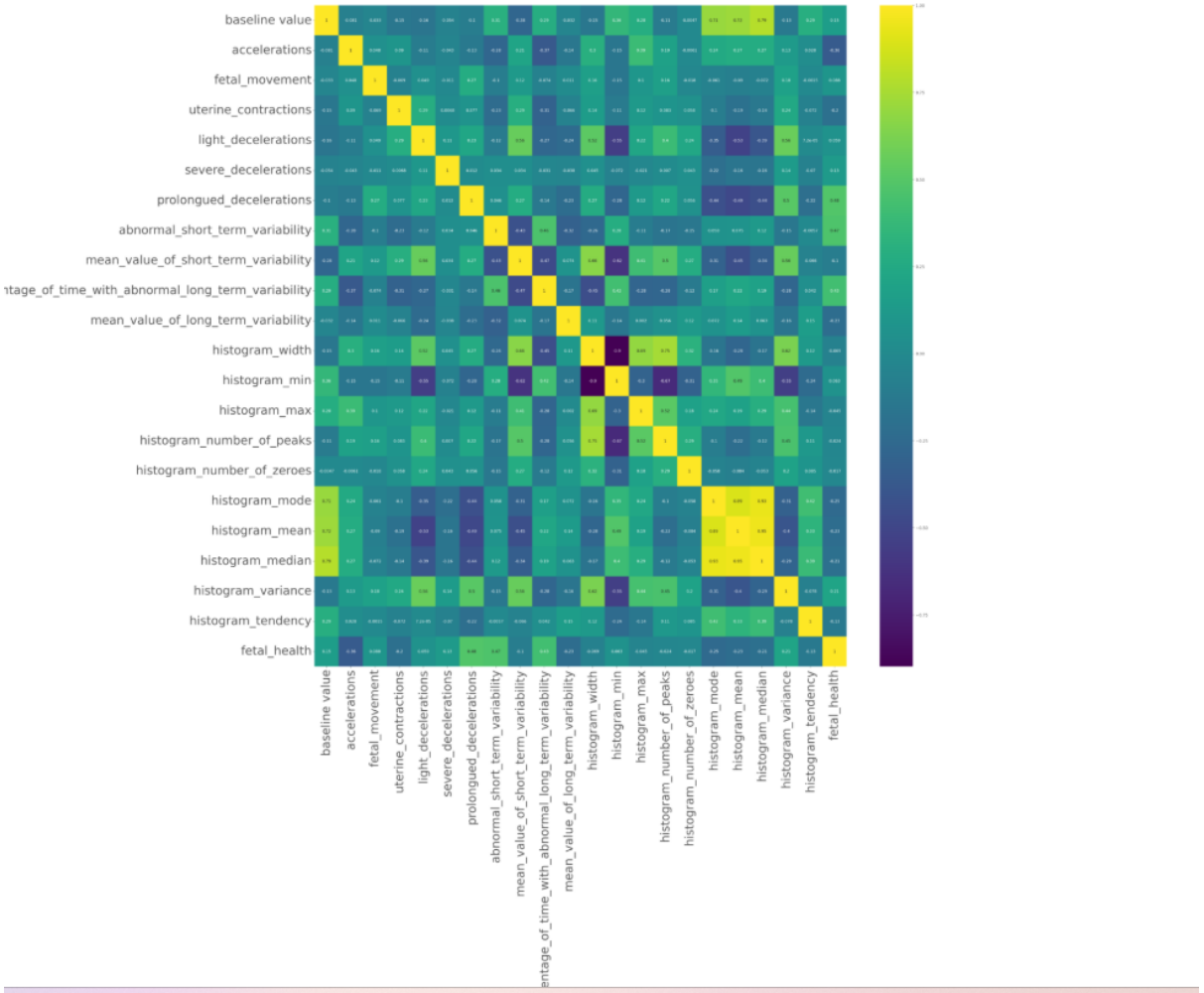

Fig 6 Correlation Heatmap of Features for Child Mortality Prediction

This heatmap visualizes the correlation between various features in the dataset used for child mortality prediction. Each cell represents the correlation coefficient between two features, with values ranging from -1 (strong negative correlation) to +1 (strong positive correlation). The color gradient, from dark purple (low correlation) to yellow (high correlation), helps identify strong relationships between features. Understanding these correlations is crucial for feature selection and engineering, as highly correlated features may contribute to redundancy in predictive modeling. This analysis aids in improving model efficiency and interpretability by identifying the most influential factors impacting fetal health.

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Random Forest

Accuracy: 0.9460

Classification Report:

	precision	recall	f1-score	support
0.0	0.96	0.98	0.97	333
1.0	0.88	0.78	0.83	64
2.0	0.93	0.93	0.93	29
accuracy			0.95	426
macro avg	0.92	0.90	0.91	426
weighted avg	0.94	0.95	0.94	426

Matthews Correlation Coefficient: 0.8474

Confusion Matrix:

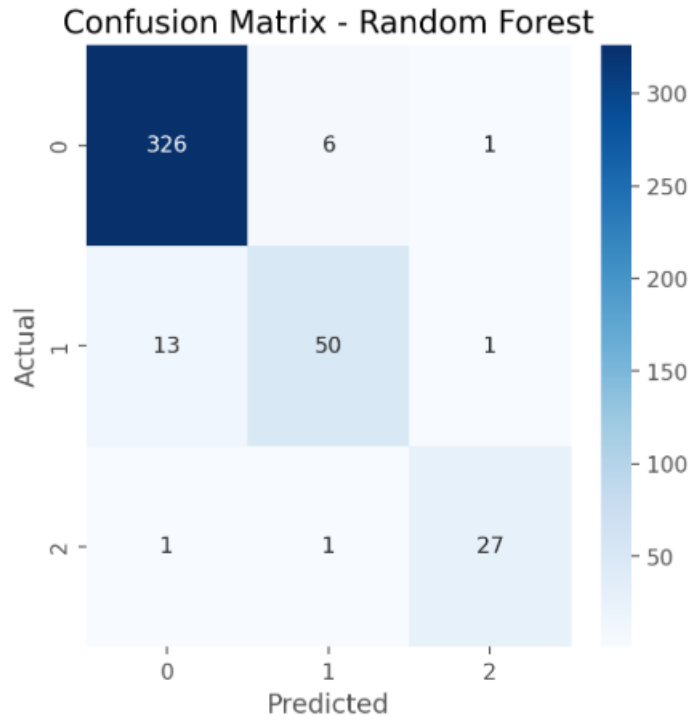

Fig 7 Random Forest Model Performance Evaluation

This report presents the performance of a Random Forest classification model applied to child mortality prediction. The model achieved an accuracy of 94.6%, indicating strong predictive capabilities. The classification report details precision, recall, and F1-score for each class, with Class 0 having the highest performance metrics. The Matthews Correlation Coefficient (MCC) of 0.8474 suggests a well-balanced model.

The confusion matrix visually represents model predictions against actual values, showing that most instances were correctly classified. However, some misclassifications occurred, particularly in Class 1, where 13 samples were incorrectly predicted as Class 0. These insights help refine the model by addressing class imbalances and improving feature selection.

5. CONCLUSION:

The study on predictive analytics for child mortality effectively demonstrates the power of machine learning in addressing critical public health issues. By leveraging models such as Logistic Regression, Support Vector Machine (SVM), and Random Forest, the research highlights how data-driven insights can be used to predict child mortality risks and support early intervention strategies. The preprocessing techniques, including feature scaling and encoding, enhance model performance, ensuring robust and accurate predictions. The evaluation metrics—accuracy, confusion matrices, ROC curves, and Matthews Correlation Coefficient (MCC)—validate the effectiveness of the proposed models, reinforcing their applicability in real-world healthcare scenarios. The integration of these predictive models into healthcare decision-making frameworks can aid policymakers and medical professionals in identifying high-risk cases and implementing timely interventions. Furthermore, this study underscores the potential of artificial intelligence in transforming healthcare analytics by providing reliable, scalable, and efficient solutions for pressing global challenges. As future research directions, expanding the dataset, incorporating deep learning approaches, and integrating socio-economic factors could further refine prediction accuracy and enhance the overall impact of such predictive systems in reducing child mortality rates worldwide.

6. FUTURE SCOPE:

The future scope of this study lies in enhancing predictive analytics for child mortality through more advanced machine learning techniques, such as deep learning and ensemble models, to improve prediction accuracy. Integrating real-time health data from wearable devices, electronic health records, and IoT-enabled monitoring systems can further refine risk assessment. Additionally, expanding the dataset with diverse demographic and socioeconomic factors will enhance model generalizability across different regions. Future research can also focus on explainable AI (XAI) to improve model transparency, enabling healthcare professionals to trust and interpret predictions effectively. Collaboration with governments and healthcare institutions can facilitate large-scale implementation, ultimately leading to more proactive and data-driven healthcare policies aimed at reducing child mortality worldwide.

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