ISSN 2319-5991 www.ijerst.com
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Peer Reviewed, Referred & Indexed Journal

Research Paper

HEAD INJURY RISK PREDICTION USING MACHINE LEARNING

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ABSTRACT— Head injury is one of the leading causes of severe trauma and mortality worldwide, making early and accurate risk assessment essential for effective medical treatment. Traditional methods of identifying the severity of head injuries rely on clinical observation and manual evaluation of multiple patient parameters, which can be time-consuming and may lead to delayed decision-making in emergency situations. To address this challenge, the proposed project, "Head Injury Risk Prediction Using Machine Learning," presents an intelligent decision-support system that predicts the risk level of head injury using a supervised machine learning approach. The proposed system employs the Logistic Regression algorithm, a simple, interpretable, and computationally efficient supervised learning model, to classify patients into High Risk or Low Risk categories. The prediction is based on important clinical parameters collected during the initial medical assessment, such as patient age, Glasgow Coma Scale (GCS) score, loss of consciousness, vomiting, skull fractures, amnesia, and other relevant indicators associated with traumatic brain injury. These parameters are provided through a user-friendly web-based application developed using Flask, HTML, and CSS, allowing healthcare professionals to enter patient information quickly and receive immediate predictions. The system preprocesses the input data, applies the trained Logistic Regression model, and generates accurate risk predictions within a

short time. Compared to traditional manual assessment methods, the proposed solution reduces decision-making time, minimizes human error, and provides consistent and reliable predictions that assist medical professionals during the initial triage process. The lightweight nature of the Logistic Regression algorithm also makes the system suitable for deployment on resource-constrained environments without requiring high computational power. The performance of the proposed model is evaluated using standard machine learning evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix to ensure reliable classification performance. The results demonstrate that Logistic Regression provides an effective balance between prediction accuracy, interpretability, and computational efficiency, making it an appropriate choice for healthcare decision-support applications. The proposed system has the potential to improve early clinical decision-making, support emergency medical personnel in prioritizing patient care, and contribute to faster diagnosis and treatment of traumatic brain injuries.

Index Terms – Head injury risk prediction, Logistic Regression, machine learning, traumatic brain injury (TBI), Glasgow Coma Scale (GCS), clinical decision support system, healthcare analytics, risk classification, Flask web application, supervised learning, emergency healthcare, medical diagnosis.

I. INTRODUCTION

Head injury, also known as Traumatic Brain Injury (TBI), is one of the leading causes of death and long-term disability worldwide. Every year, millions of people suffer head injuries due to road accidents, sports injuries, falls, workplace incidents, and other traumatic events. Early identification of patients who are at high risk of developing serious brain injuries is extremely important because timely medical intervention can significantly improve patient outcomes and reduce mortality rates. However, accurately assessing the severity of head injuries during the initial stages remains a challenging task for healthcare professionals. Traditionally, doctors rely on clinical examinations, patient symptoms, and standardized medical decision rules such as the Canadian CT Head Rule, CATCH, CHALICE, and PECARN to evaluate the risk of traumatic brain injuries. Although these methods have proven effective, they require healthcare professionals to manually analyze multiple clinical parameters before making a decision.

This manual assessment process can be time-consuming, especially in busy emergency departments where rapid decision-making is critical. Recent advancements in Machine Learning (ML) have opened new possibilities for developing intelligent healthcare decision-support systems. Machine learning algorithms are capable of identifying meaningful patterns from historical clinical data and making accurate predictions based on previously learned information. Among various supervised learning algorithms, Logistic Regression is widely recognized for its simplicity, interpretability, computational efficiency, and effectiveness in solving binary classification problems.

The proposed project, "Head Injury Risk Prediction Using Machine Learning," presents a web-based clinical decision-support system that predicts whether a patient belongs to the High Risk or Low Risk category based on important clinical parameters. The system accepts patient information such as age, Glasgow Coma Scale (GCS) score, loss of consciousness, vomiting, skull fractures, amnesia, and other medically relevant indicators through an intuitive web interface developed using Flask, HTML, and CSS. These clinical parameters are processed using a trained Logistic Regression model, which provides accurate and reliable risk predictions within a few seconds. By combining machine learning techniques with a user-friendly healthcare application, the proposed system assists medical professionals in making faster, more consistent, and evidence-based clinical decisions.

The system reduces manual effort, minimizes the possibility of human error, and supports early identification of patients requiring immediate medical attention. Its lightweight design and computational efficiency also make it suitable for deployment in hospitals, emergency departments, rural healthcare centers, and other resource-constrained environments where rapid risk assessment is essential.

II. RELATED WORK

A. Identification of Children at Very Low Risk of Clinically Important Brain Injuries after Head Trauma: A Prospective Cohort Study

This study introduced the PECARN (Pediatric Emergency Care Applied Research Network) clinical decision rule for identifying children who are at very low risk of clinically important traumatic brain injuries. The research analyzed over forty thousand pediatric patient records using clinical parameters such as Glasgow Coma

Scale (GCS), vomiting, loss of consciousness, severe injury mechanism, and signs of skull fracture. The proposed decision rule achieved excellent sensitivity while significantly reducing unnecessary CT scans. The study demonstrated that structured clinical information can effectively support early diagnosis without depending solely on radiological imaging. This work serves as one of the most influential clinical foundations for modern head injury prediction systems and has inspired many machine learning-based healthcare decision-support applications.

B. The Canadian CT Head Rule for Patients with Minor Head Injury

This research proposed the Canadian CT Head Rule (CCHR) to help physicians determine whether patients with minor head injuries require CT imaging. The study identified important clinical risk factors including age, vomiting, skull fractures, Glasgow Coma Scale score, amnesia, and dangerous injury mechanisms.

The decision rule successfully reduced unnecessary CT scans while maintaining high diagnostic sensitivity for serious brain injuries. The research highlighted that structured clinical indicators can provide reliable support for emergency physicians during patient triage and remains one of the most widely adopted head injury assessment guidelines worldwide.

C. Children's Head Injury Algorithm for the Prediction of Important Clinical Events (CHALICE)

The CHALICE clinical decision rule was developed to improve the identification of significant head injuries in pediatric patients presenting to emergency departments. The proposed algorithm combines patient history, physical examination findings, neurological assessment, and injury mechanisms to predict clinically important traumatic brain injuries. The study demonstrated that systematic evaluation of multiple clinical indicators improves diagnostic accuracy while minimizing unnecessary imaging procedures. CHALICE has become one of the most frequently referenced clinical decision rules for pediatric head injury assessment and has contributed significantly to the development of intelligent medical decision-support systems.

D. Statistical and Machine Learning Approaches to Predict Outcomes in Traumatic Brain Injury

This research reviewed several statistical and machine learning techniques for predicting outcomes in patients with traumatic brain

injury. Multiple supervised learning algorithms, including Logistic Regression, Random Forest, Support Vector Machine, and Gradient Boosting, were evaluated using clinical datasets. The study emphasized that machine learning models can effectively support clinical decision-making by analyzing complex patient information and identifying important predictive factors. It also highlighted the importance of model interpretability, data quality, and computational efficiency when deploying machine learning systems in healthcare environments. The findings support the use of interpretable models such as Logistic Regression for clinical decision-support applications.

III. PROPOSED METHODOLOGY

The proposed Head Injury Risk Prediction Using Machine Learning system utilizes the Logistic Regression algorithm to predict whether a patient is at High Risk or Low Risk of traumatic brain injury based on important clinical parameters. The system collects patient information such as age, Glasgow Coma Scale (GCS) score, loss of consciousness, vomiting, skull fracture, amnesia, seizure history, and other relevant medical indicators through a simple web-based interface developed using Flask, HTML, and CSS. After receiving the input, the system preprocesses the data and applies the trained Logistic Regression model to generate a fast and reliable prediction. The lightweight nature of Logistic Regression makes the system computationally efficient while maintaining good interpretability and consistent performance for binary classification problems. Logistic regression is widely used in clinical risk prediction because of its transparency and ability to estimate probabilities for binary outcomes.

The proposed system aims to assist healthcare professionals by providing quick decision support during the initial assessment of patients with head injuries. Instead of replacing medical expertise, the application serves as an intelligent clinical decision-support tool that helps doctors identify high-risk patients who may require immediate medical attention or further diagnostic procedures. The model is trained using structured clinical data and evaluated using standard machine learning performance metrics such as Accuracy, Precision, Recall, F1-Score, and Confusion Matrix to ensure reliable predictions. The web-based implementation enables easy deployment in hospitals, emergency departments, and rural healthcare centers, providing a cost-effective and user-friendly solution for early head injury risk assessment. Machine learning has

shown strong potential for supporting prognosis and risk prediction in traumatic brain injury when used alongside established clinical assessment methods.

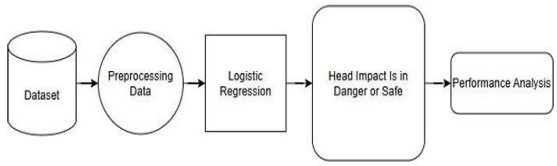


Fig. 1: System Overview

1. Data Collection Module

Clinical data related to head injury patients is collected from structured datasets and patient records containing important medical parameters. The collected attributes include Age, Glasgow Coma Scale (GCS), Loss of Consciousness, Vomiting, Skull Fracture, Amnesia, Seizure History, and other clinically significant observations required for risk prediction.

2. Data Preprocessing Module

The collected clinical dataset undergoes preprocessing to remove missing values, inconsistencies, duplicate records, and invalid entries. The data is transformed into a machine-readable format suitable for training the Logistic Regression model, ensuring improved prediction accuracy.

3. Feature Selection Module

Relevant clinical features are selected based on their importance in predicting traumatic brain injury risk. The selected parameters improve the overall model performance by eliminating unnecessary attributes and reducing computational complexity.

4. Machine Learning Model Training Module (Logistic Regression)

The Logistic Regression algorithm is trained using historical clinical data to learn the relationship between patient symptoms and head injury severity. The trained model identifies patterns in patient data and predicts whether a patient belongs to the High Risk or Low Risk category.

5. Risk Prediction Module

The trained Logistic Regression model processes newly entered patient information and predicts the probability of head injury risk. Based on the prediction score, the system classifies the patient as either High Risk or Low Risk, supporting faster clinical decision-making.

6. Web Application & Result Display Module

A Flask-based web application provides a simple interface where healthcare

professionals can enter patient clinical details. The prediction result is displayed instantly with the corresponding risk category, enabling quick and reliable clinical assessment.

7. System Evaluation Module

The performance of the proposed system is evaluated using standard machine learning metrics such as Accuracy, Precision, Recall, F1-Score, and Confusion Matrix. These evaluation metrics help verify the reliability, consistency, and effectiveness of the Logistic Regression model in predicting head injury risk.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed Logistic Regression-based head injury prediction model accurately classifies patients into High Risk and Low Risk categories using clinical parameters such as Glasgow Coma Scale (GCS), age, loss of consciousness, and skull fracture history. Performance evaluation using accuracy, precision, recall, F1-score, and confusion matrix demonstrates reliable and consistent classification. The lightweight model provides fast predictions with low computational overhead, making it suitable for real-time clinical decision support. Overall, the proposed framework offers an efficient and interpretable solution for early head injury risk assessment and emergency healthcare management.



Fig. 2: Login

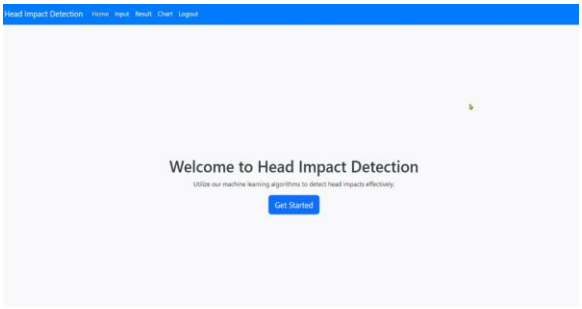


Fig. 3: Home Page

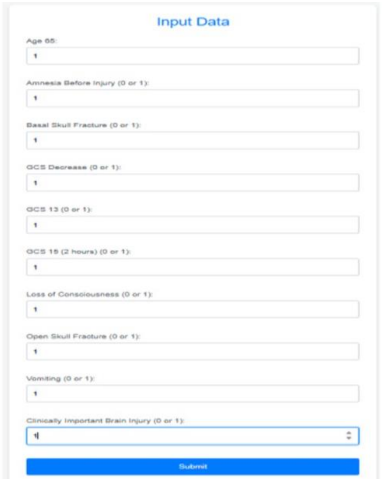


Fig. 4: Enter Input Data

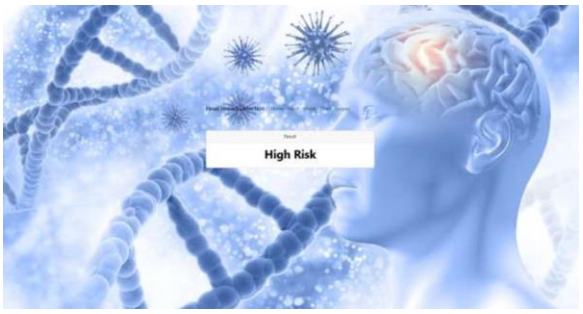


Fig. 5: Result

V. CONCLUSION

In conclusion, this project demonstrates the effectiveness of **Logistic Regression** for accurately detecting head impacts using sensor data, achieving high performance with 90% accuracy. The simplicity, interpretability, and computational efficiency of Logistic Regression make it a promising solution for real-time safety applications, especially in environments where rapid decision-making is critical. By leveraging a systematic approach that includes data preprocessing, feature engineering, and rigorous evaluation, the model is well-suited for deployment in both sports and industrial contexts, where head injuries need to be detected promptly to prevent further harm. While the model's performance is already robust, future enhancements, such as integrating more advanced feature engineering, optimizing model parameters, and incorporating real-time learning, could further increase its accuracy and adaptability. The insights gained from this study contribute to the broader goal of developing intelligent safety systems that utilize wearable technology and machine learning to improve safety and decision-making, ultimately reducing the risks associated with head impacts and enhancing overall protective measures in various high-risk environments.

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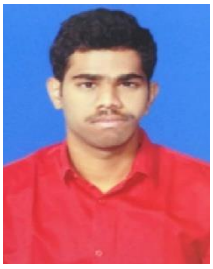
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