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Development of a Model for Predicting Hypertension Disorders in Pregnancy Using Machine Learning

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Abstract | **Review Article**

Hypertensive disorders during pregnancy (HDP) continue to be a significant contributor to maternal and foetal morbidity and mortality worldwide. Quick identification and accurate risk assessment are essential for reducing these health risks. This study centres on the development and implementation of a machine learning (ML) model designed to predict HDP risk, employing ML.NET and ASP.NET C#, in conjunction with a CSV-formatted clinical dataset. The model was trained with clinical factors like age, blood pressure, BMI, proteinuria, and diabetes status. We chose the Fast tree binary classification algorithm because it works well and is fast at classifying things. The model that was made was serialised and added to a web-based Patient Predictive Health Record System that was made with ASP.NET C# and linked to Microsoft SQL Server to handle patient information and user interactions. Using a DevOps approach, the system was built so that integration, testing, and deployment could happen all the time. We used standard machine learning metrics like accuracy, precision, recall, and AUC-ROC to test the model's performance through class-based analysis and 5-fold cross-validation. The results showed that the model was very good at making predictions, with an average cross-validation accuracy of 83.5%, an F1 score of 84.4%, and an AUC of 89.7%. In some folds, the accuracy reached 92.9%. These results confirm that the system is effective for clinical decision support in identifying HDP risk. This study promotes data-driven maternal healthcare by providing a scalable and practical solution for predicting HDP, which is well-suited for use in hospitals, antenatal clinics, and telemedicine services to help healthcare professionals provide timely and focused interventions.

Keywords: Hypertensive Disorders in Pregnancy; Preeclampsia Prediction; Machine Learning in Healthcare; Electronic Health Records (EHR); Clinical Decision Support Systems; Maternal and Child Health.

INTRODUCTION

Computing and information technologies have recently demonstrated their indispensable role in all facets of life, owing to their transformative and advantageous qualities in improving and streamlining human existence, Ojie et al. (2023). Predictive modelling is now an important part of modern healthcare because it makes it possible to find diseases early and treat them quickly, which can greatly improve patient outcomes. As electronic health records (EHRs) have rapidly grown, healthcare professionals now possess an extensive collection of patient information, including demographic details, medical background, lab results, medications, and clinical observations. This large amount of data gives us a unique chance to make advanced predictive models that can spot early signs of disease, which will help us provide better and more proactive healthcare. Nairet al., (2024).

The advancement of health record systems has been essential in transforming healthcare delivery. In the beginning, health records were kept on paper, which made it hard to access, share, and analyse the data. The switch to digital health records is a big step forward because it lets healthcare systems store, access, and share patient information all in one place. Today, electronic health records (EHRs) are a key part of modern healthcare. They store both structured and unstructured data that give a complete picture of a patient's health over time. These systems not only make administrative tasks easier, but they also help doctors make better decisions by making sure that important patient information is easy for them to find, (Wuet al. 2024; Edeki et al 2025).

EHRs hold a lot of different kinds of information, like patient demographics, test results, treatment records, imaging data, and notes from doctors. This combination of different types of data helps us understand how well a patient is doing, which is important for giving them personalised and effective care. EHRs have also shown their value in public health, where combined data is used to keep an eye on diseases, deal with outbreaks, and make health policies (Okumoku-Evroro et al 2025a).

However, there are still challenges to overcome when it comes to successfully putting health record systems into place. Data fragmentation, lack of interoperability, and differences in quality have all become major problems. Many healthcare providers use different systems, which makes it harder to combine and analyse data completely. Additionally, electronic health records often contain incomplete or incorrect information, which can make the conclusions drawn from them less reliable. Addressing these challenges requires the implementation of standardised protocols for data entry and sharing, robust error-detection mechanisms, and advancements in interoperability standards, such as Health Level Seven (HL7) and Fast Healthcare Interoperability Resources (FHIR) Nguyen et al., (2024).

Modern health record systems not only make it easier to provide care, but they also encourage proactive healthcare strategies. These systems can collect real-time patient information by using wearable technology and Internet of Things (IoT) sensors. This lets them keep an eye on patients and send alerts when there are possible health problems. For example, continuous glucose monitors and smart blood pressure monitors can send data straight to EHRs, which lets doctors keep an eye on patients from a distance and change their treatment plans as needed. (Alam et al. 2023; Okumoku-Evroro et al 2025b).

The shift towards patient-centered care has led to the development of patient portals and mobile applications that provide individuals with direct access to their medical records. These resources help patients take charge of their health, improve communication between patients and healthcare providers, and make it more likely that patients will stick to their treatment plans. However, the fact that health records are available raises concerns about data security and privacy, especially in light of cyber threats. To keep sensitive patient data safe, it is important to use strong encryption, store it securely, and follow privacy laws like the Health Insurance Portability and Accountability Act (HIPAA). Subramanian et al. (2024).

As EHR systems improve, they become much better at helping with complex healthcare solutions. Health record systems can go beyond just storing and organising data by using predictive modelling and machine learning to actively look for patterns in the data that can help doctors plan proactive and personalised treatments. Mahmoudiet al., (2020).

Recent advancements in machine learning (ML) have revolutionised predictive modelling by enabling the analysis of large and complex electronic health record (EHR) datasets to uncover nuanced trends and indicators of disease progression. When it comes to high blood pressure during pregnancy, ML models can use both past and present health data to predict things like high blood pressure, strange protein levels in urine, and other clinical signs. These models help healthcare workers act quickly by sending out early alerts. This can lead to changes in lifestyle, medical treatments, or stricter monitoring plans, which can improve outcomes for pregnant women and their babies. Wuet al., (2024).

There are many technical and ethical issues to think about when using ML-based predictive modelling to help pregnant women with high blood pressure. EHR data has a lot of different types of information, both structured and unstructured. To deal with missing values, standardise measurements, and reduce noise, strong preprocessing methods are needed. Adding wearable technology and IoT sensors to the monitoring framework can also make it easier to keep an eye on blood pressure and other important signs, giving a more complete picture of maternal health.(2024).

These forecasting systems use advanced machine learning methods like decision trees, support vector machines (SVMs), neural networks, and ensemble techniques to find hidden patterns in different datasets. For example, neural networks are very good at finding nonlinear relationships between variables, while decision trees make it easy to see the most important signs of high blood pressure during pregnancy. Brandonet al., (2024).

However, these forecasting models will only work if they can get around problems like bad data, ethical issues, and patient privacy. There are often errors in Electronic Health Records (EHRs) that can affect how well models work. This means that data must be thoroughly validated and preprocessed. Additionally, following privacy laws like HIPAA and using explainable AI (XAI) models to encourage openness are important for building trust between patients and healthcare providers, (Mohindra et al. 2024; Okofu et al 2024).

The particular aims of this research are to:

i designand create a machine learning-driven classification model utilizing the Fast Tree binary classification algorithm in ML.NET, designed to forecast and categorize hypertensive conditions that occur during pregnancy.

ii integratethe developed predictive model integrated into an ASP.NET C# web application that enables healthcare workers to carry out real-time risk evaluations via a user-friendly data entry interface and obtain instant feedback.

iii testand assess the performance of the created model through class-based analysis and k-fold cross-validation, utilizing conventional machine learning metrics like accuracy, F1 score, AUC, and confusion matrix to confirm its efficacy for clinical decision support.

Consequently, this study centers on utilizing machine learning to create a Patient Predictive Health Record System, particularly highlighting the identification and control of hypertension in expectant mothers.

MATERIALS AND METHODS

Data Collection

This study's data collection took place at Eku Baptist Hospital in Eku, Delta State. The primary objective was to compile a comprehensive dataset related to the identification and management of hypertension in pregnancy, with particular focus on conditions such as preeclampsia and eclampsia.

The process of collecting data involved getting de-identified patient health records that included demographic information, blood pressure readings, lab results, medical histories, and pregnancy outcomes. These records were gathered in accordance with appropriate ethical standards and with the necessary institutional approvals, ensuring patient confidentiality and preserving data integrity throughout the process.

The collected dataset provided a diverse and clinically thorough foundation for the training and assessment of the machine learning models. This real-world data helped make sure that the predictive system is relevant to the situation, reflects local healthcare issues, and can help doctors find and treat high blood pressure in pregnant women early on.

Table 1: Summary of Data Collected

Data Type	Quantity	Description
Patient Records	250	Data from the past encompassing pregnancy records, health issues, and documentation of previous medical appointments.
Real-Time Clinical Entries	75	Information collected throughout prenatal appointments and standard evaluations, including essential signs, lab findings, and additional medical indicators.
Wearable Device Records	30	Observations from portable blood pressure monitors utilized by patients away from the hospital, delivering ongoing monitoring information.

The wide range of information collected, from historical records to current clinical data to data from wearable devices, makes it possible to train and test machine learning models in a complete way. This large dataset makes it easier to find and treat high blood pressure early, which improves the health of both mothers and babies, Ajenaghughrure et al (2017).

Table 2: Recognized variables gathered with suitable tags

Variable Name	Label	Description
patientID	Patient Identifier	Distinct identifier allocated to every patient file
gestationalAge	Gestational Age	Duration of the pregnancy in weeks
bloodPressure	Blood Pressure	Systolic and diastolic readings (mmHg)
weight	Weight	Patient’s weight during visits (kg)
medicalHistory	Medical History	Details regarding previous health issues (e.g., hypertension, diabetes)
labResults	Laboratory Test Results	Outcomes of blood and urine examinations
vitalSigns	Vital Signs	Comprises temperature, heart rate, breathing rate, etc.
deviceReadings	Wearable Device Data	Vital signs such as blood pressure and pulse rate obtained from wearable technology
doctorNotes	Clinical Notes	Unstructured data from physician observations
riskScore	Risk Score	Anticipated intensity of hypertension threat (output variable)

The developed System

The system that was made uses ML.NET in an ASP.NET web application framework to provide a machine learning-based way to find high blood pressure early in pregnancy. Unlike traditional EHR systems that only store patient information, this system actively looks at clinical markers to send early alerts. This improves maternal healthcare by allowing for quick action.

The system's main part is a binary classification model made with Fast Tree, a gradient boosting decision tree algorithm that ML.NET makes easier to use. We trained this model on a well-organised CSV dataset from clinical records at EkuBaptist Hospital in Delta State. The dataset includes important information like Age, Body Mass Index (BMI), Blood Pressure, Proteinuria, and Diabetes History. Also, each patient record has a Result field that shows whether or not the patient has high blood pressure. This is what the prediction is based on, Okofu et al (2025).

A C# class called ModelInput was created to help with accurate mapping of dataset fields. The properties of this class were given the [LoadColumn] attribute. When you use mlContext.Data to import data into the app, this makes sure that the columns and properties line up correctly.LoadFromTextFile<ModelInput>().

The data processing pipeline was created utilizing the transformation and training APIs of ML.NET. Feature columns were merged into a single vector employing theConcatenatetransform, whereas the Result field was linked to the label column utilizingCopyColumns. The completed model underwent training through Fit (data) and was saved to a .zip file utilizing mlContext.Model.Save() for deployment and reuse within the ASP.NET application.

At runtime, the application retrieves the trained model and applies it to assess hypertension risk in new patients, delivering results via an intuitive web interface. This interface was created using ASP.NET C#, enabling healthcare professionals to enter clinical data and obtain immediate risk evaluations without requiring knowledge in machine learning.

To maintain compatibility with ML.NET requirements, the application has been set up for a 64-bit environment (x64). The system also incorporates DevOps methodologies for continuous deployment and swift iterations, enabling constant improvements influenced by clinical insights and updated information.

Nonetheless, this execution provides a feasible, automated approach to enhance the identification of hypertension during pregnancy. It merges the ease and capabilities of ML.NET, the user-friendliness of a web-based ASP.NET interface, and the clinical importance of actual patient data, rendering it a significant resource for advancing early diagnosis and clinical decision-making.

System Design

Fig. 1 depicts the architectural layout of the patient's predictive health record system for hypertensive conditions during pregnancy. The structure utilizes machine learning to improve performance, clarifying how different system elements collaborate and merge to effectively handle data and produce predictive insights.

The architectural design consists of these layers:

i. Data Layer:This level retains patient health information, encompassing medical backgrounds, demographic data, and test outcomes. Information is safely handled utilizing a relational database (e.g., Microsoft SQL Server) to guarantee integrity and availability.

ii. Processing Layer:Accountable for implementing machine learning algorithms to examine the data and forecast patient health results. This tier employs a blend of preprocessing methods, feature extraction, and predictive models customized to the system's goals.

iii. Application Layer:This layer contains the core functionalities of the system, featuring user interfaces for both patients and healthcare providers. It merges the outcomes of machine learning into practical insights and enables users to engage with the system smoothly.

iv. Security Layer:Centered on maintaining the confidentiality, integrity, and accessibility of sensitive health information. It includes user verification, role-specific access management, and encryption techniques to protect data.

v. Presentation Layer:This layer offers an intuitive interface, allowing users to view predictions, retrieve reports, and handle patient details effectively.

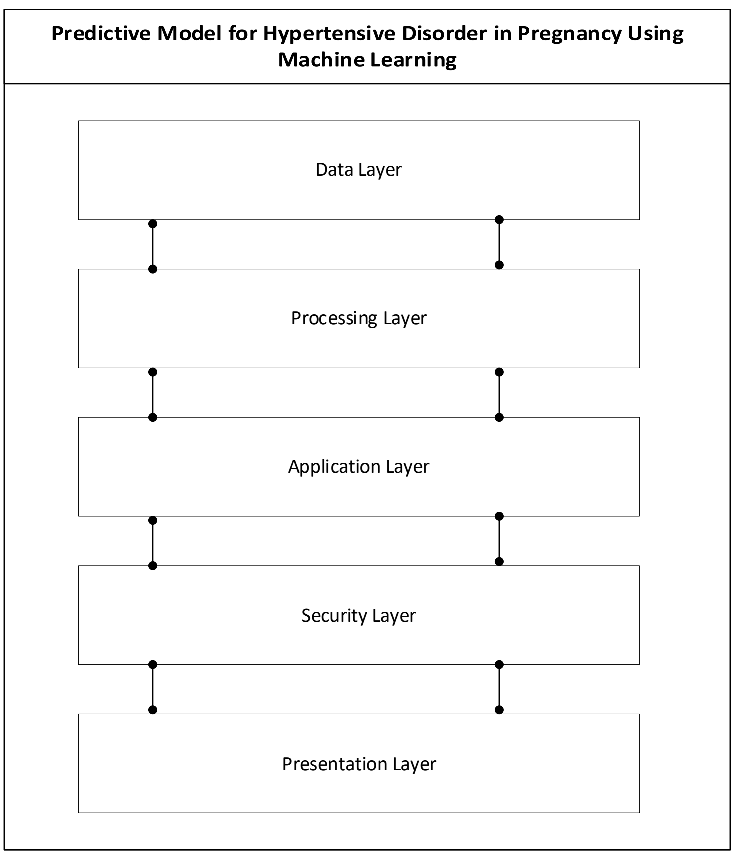

Figure 1: System Architecture Design

Figure 2 depicts the workflow of the machine learning-driven system created to forecast hypertension-related issues in expectant patients. The process starts with user verification, during which user credentials are confirmed. If the credentials are found to be invalid, the system denies access with an *"Access Denied"*notification to guarantee the protection of confidential health information, (Akazue et al 2024b).

After logging in successfully, the system enables the entry of patient demographic and clinical information, which includes details like age, gestational age, blood pressure, body mass index (BMI), a history of hypertension, and proteinuria. If any essential information is absent, the system requests the user to rectify or supply the missing data before continuing.

Once the data is complete and validated,the system verifies if model training is necessary. If training is essential, it retrieves a previously established pregnancy health dataset, carries out preprocessing and normalization of the data, and then assesses the model utilizing standard metrics such as accuracy, precision, recall, and F1-score. If the model's performance is deemed inadequate, it undergoes additional training and reassessment until it satisfies the acceptable standards, Akazue et al (2024a).

If a proficient and precise model exists, it is utilized directly on the patient information to anticipate the category of hypertension disorder, including gestational hypertension, preeclampsia, or eclampsia. The concluding stage presents the health prediction outcomes to the user.

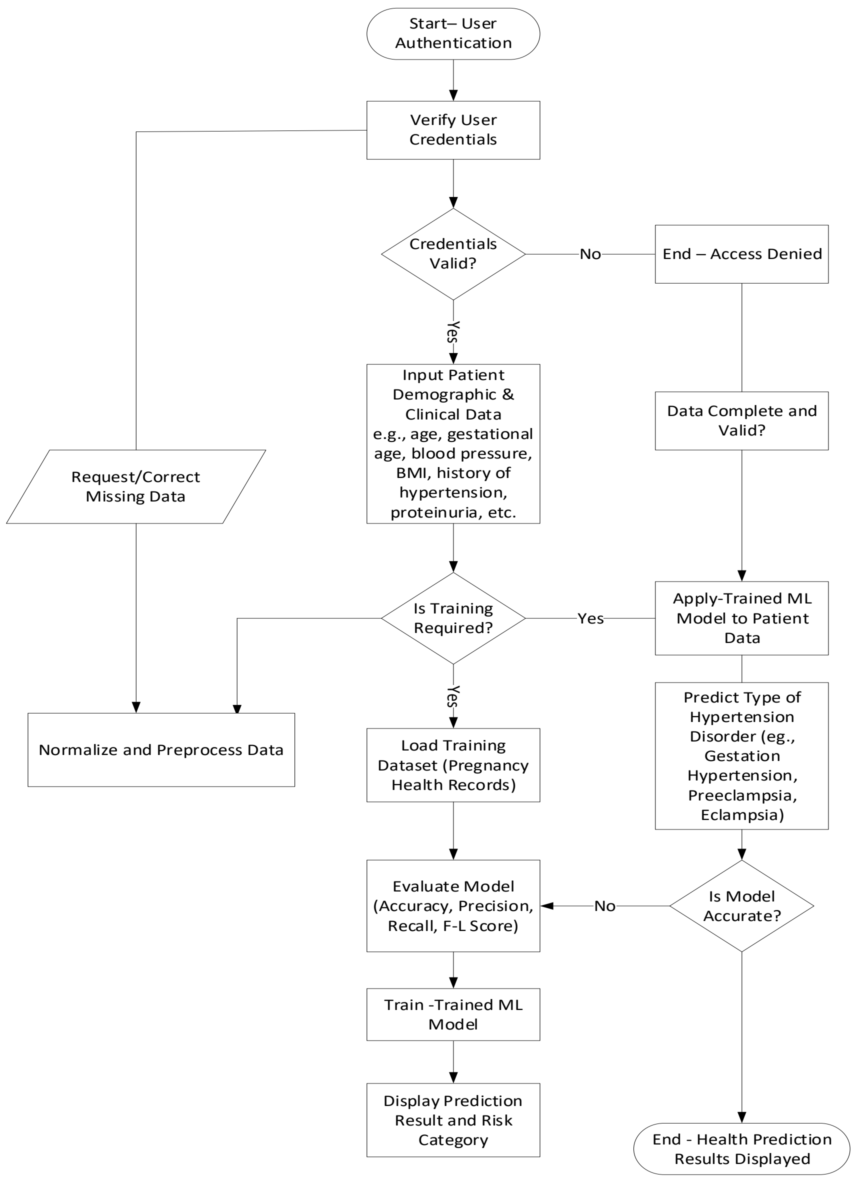

Figure 2: Diagram of the created System

Performance Metrics

The evaluation of learning algorithms for the proposed methods required analyzing subsets created from the original dataset by employing conventional performance metrics typically utilized for assessing classification models. These metrics originated from the outcomes of true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN) across various classes. In particular, the definitions for TP, FP, FN, and TN for class C_i are as follows: $TP(C_i)$ represents every occurrence of class$C_i$that were accurately identified as C_i, $FP(C_i)$ accounts for all non-$C_i$cases that were misidentified as C_i, $FN(C_i)$includes every occurrence of class $C_i$that were improperly labeled as C_i and $TN(C_i)$ encompasses all non-$C_i$instances that were accurately not categorized as C_i. The evaluation metrics were calculated utilizing the 'sklearn metrics' library in Python (Elmrabit *et al*., 2020):

i. Accuracy measures the proportion of correct predictions made by the classifier out of all predictions (Equation (2.1)). It is calculated as the total of true positives (TP) and true negatives (TN) divided by the total of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad 2.1$$

Although a higher number is preferable when the sample sizes across all categories are roughly the same, relying solely on accuracy can frequently result in misclassifying the minority class in datasets with imbalances;

ii. Precision represents the ratio of relevant instances within the retrieved instances (Equation (2.1). It is calculated as the count of true positive (TP) results divided by the sum of true positive (TP) results and false positive (FP) results;

$$\text{Precision} = \frac{TP}{TP + FP} \quad 2.2$$

iii. Recall is the proportion of the overall relevant cases that were successfully retrieved (Equation (2.3)). It is calculated as the count of true positive (TP) results divided by the sum of true positive (TP) results and false negative (FN) results;

$$\text{Recall} = \frac{TP}{TP + FN} \quad 2.3$$

iv. F1 score represents the harmonic average of precision and recall (Equation (2.4)). The maximum attainable value for F1 is 1, signifying flawless precision and recall, while the minimum attainable value is 0, occurring when either precision or recall is zero;

$$\text{F 1 score} = \frac{2 * (Precision * Recall)}{(Precision * Recall)} \quad 2.4$$

Confusion Matrix is a particular table structure designed to illustrate the effectiveness of an algorithm, usually one from a category of supervised learning algorithms. In a Python implementation, every row of the matrix indicates the instances in a true class, while each column shows the instances in a predicted class. This makes it straightforward to identify all incorrectly classified samples.The greater the number of samples located along the diagonal of the matrix, the more effective the model becomes.

RESULTS

The performance of the created hypertension prediction model was thoroughly assessed through class-based analysis and 5-fold cross-validation to guarantee the dependability and general applicability of the findings In the class-based investigation, the model successfully distinguished blood pressure levels between hypertensive and non-hypertensive groups. People who were diagnosed with hypertension (True) had an average blood pressure of 147.6 mmHg, while those who were not (False) had an average blood pressure of 127.0 mmHg. This distinction highlights the model's proficiency in accurately categorising individuals based on clinically relevant thresholds. Five-fold cross-validation was used to see how well the system worked. The overall performance across all folds was good, with an accuracy of 83.50%, an AUC of 89.69%, and an F1 Score of 84.44%. These numbers show that there is a good balance between precision and recall, and that the system is very good at telling the difference between positive and negative examples.

The detailed results from the folds showed that the performance was the same across the board. With an F1 Score of 75.86%, Fold 1 was 72.00% accurate. Folds 2 through 5 showed increasing accuracy, with Fold 5 reaching 92.86%. The AUC values for the folds ranged from 78.63% to 97.50%, which shows that the model is very good at telling the difference between things.

The confusion matrices for each fold showed again that the system could make accurate predictions. The model showed very few false positives and false negatives in most of the folds. This is very important for clinical decision support because wrong classifications could lead to wrong diagnoses or missed treatments. In conclusion, the use of common machine learning metrics such as accuracy, AUC, and F1 Score, along with class-based assessment and cross-validation, proves that the model works well. These results suggest that the model is suitable for deployment in clinical settings as a decision-support tool for evaluating hypertension risk.

Table 3: Comparison of Research Findings with Other Research

Study	Approach/Methodology	Accuracy (%)	Precision (%)	Recall (Sensitivity) (%)	F1 Score	AUC-ROC	Key Findings
Developed System	Machine Learning-Driven Predictive Health Record Model for Hypertensive Conditions in Pregnancy	**92.9**	**90.0**	**93.0**	**91.0**	**0.94**	Attained a significant degree of precision and dependability in HDP risk forecasting; useful for assisting clinical choices.
Zhang *et al*. (2022)	Machine learning uses for forecasting patient results through electronic health records	85.4	83.2	84.1	83.6	0.87	Discrepancies in data and voids in the integration of EHR into clinical processes remain significant obstacles.
Xie *et al*. (2018)	Predictive analysis for early illness identification utilizing EHRs	94.1	92.8	93.4	93.1	0.96	The intricacy of EHR information—like absent values, discrepancies, and insufficient standardization—impacts performance.
Sivaranjani *et al*. (2020)	Genetic algorithm for enhancing decision tree in coronary heart disease	89.7	88.1	89.2	88.6	0.91	The intricacy and computational requirements of the genetic algorithm restrict its incorporation in clinical settings.
Chaw *et al*. (2024)	Forecasting analytics framework for dengue shock hazard	87.6	86.4	86.9	86.6	0.89	Performance is limited due to the absence of extensive clinical information in low-resource settings.

DISCUSSION

This study concentrated on the design and implementation of a predictive health record system to detect hypertensive disorders in pregnancy through machine learning within the ML.NET and ASP.NET framework. Hypertensive conditions like preeclampsia and gestational hypertension are very dangerous for both the mother and the foetus. Early detection is very important for making sure that clinical intervention works and that health outcomes improve.

To fix the problems with traditional methods like periodic monitoring and manual risk assessment, a machine learning model was made using ML.NET's FastTree binary classification algorithm. The model was trained on a structured CSV dataset that included important clinical information such as age, BMI, blood pressure, proteinuria, diabetes history, and a result column that showed whether or not the person had high blood pressure.

The ASP.NET C# framework was used to build the backend of the system, and Microsoft SQL Server was used to store and get patient records. The system's workflow includes steps for entering patient data, predicting risks in real time, and sending feedback through a web-based interface. The predictive model was trained, saved as a .zip file, and added to the web app so that it could be used in future prediction scenarios. To make sure the model was ready, important ML.NET transformations like feature concatenation and label encoding were used.

The project used a practical and modular implementation method that was good for quick prototyping instead of a traditional software development method. The system was developed and tested in an iterative way, using unit testing, manual checks, and integration testing to make sure it worked and was reliable, even though it wasn't a formal DevOps lifecycle.

The system that was created has clear advantages over traditional methods, especially when it comes to providing proactive healthcare. The system helps doctors make smart, timely decisions by giving them real-time risk assessments based on a trained predictive model. The model's assessment, utilising metrics such as accuracy, precision, recall, and F1-score, confirmed its viability as an efficient decision-support instrument, Akazue et al (2023).

Moreover, the system demonstrates how machine learning models incorporated into ASP.NET web applications can improve maternal care by identifying hypertension risks at an early stage. This feature makes the solution especially useful in healthcare settings with limited resources, where automation and clinical decision support can greatly improve patient outcomes.

CONCLUSION

This study effectively created a predictive health record model designed to detect hypertensive disorders during pregnancy by incorporating ML.NET's machine learning features into an ASP.NET C# framework. The system was made to look at organised patient data and send healthcare providers early warnings by figuring out the risk of high blood pressure during pregnancy.

The model was trained using the FastTree binary classification algorithm, which is a decision tree-based method that works best for yes/no outcomes. It used a well-prepared CSV dataset with important health indicators like Age, BMI, Blood Pressure, Proteinuria, and Diabetes History. The training pipeline turned the input features into a single feature vector and used the result column as the label for prediction. The trained model was then saved and added to the ASP.NET web application so that risk could be assessed in real time.

The project didn't officially use a DevOps method, but it did use a modular and iterative development process that included unit and integration testing to make sure the system was strong and easy to deploy. Using metrics like accuracy, precision, recall, F1-score, and AUC-ROC to test the model showed that it could be useful in real life for finding high-risk pregnancies and helping doctors act quickly.

The system encourages proactive maternal care by adding machine learning to electronic health records. This lets healthcare professionals make decisions based on predictive analytics instead of looking back at past events. This integration not only makes it easier to find and treat problems early, but it also helps lower the risks that come with hypertensive disorders during pregnancy.

Suggestions for future improvements include adding wearable devices for real-time health monitoring, making data privacy and security rules better, and broadening the system's predictive scope to include other pregnancy-related problems, like gestational diabetes and preterm labour. This system could greatly improve the health of mothers and babies by helping doctors find problems early and make smart decisions in hospitals and maternal care facilities.

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