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PREDICTING HEALTH OF FOETUS USING KNN ALGORITHM

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Abstract

Fetal wellbeing is an important issue in prenatal care because early identification of complications was implemented, and performance was measured on the basis of important metrics: accuracy, precision, recall, and F1-score. Our model had an accuracy of can greatly lower the potential 94.5%, showing its in assisting gynecologists' risk of neonatal death and long-term developmental problems. we introduce a data driven method for forecasting fetal health condition based on

the KNearest Neighbors algorithm, which is an uncomplicated yet efficient machine learning technique commonly known as the best performer in medical diagnosis. The dataset fetal cardiotocographic measurement records, including fetal heartbeat, uterine contractions, and accelerations. These inputs were obstetricians with real-time decision- making in pregnancy monitoring. project tells the ability of machine learning to improve fetal health evaluation.

KeyWords

Fetal health prediction, K-Nearest Neighbors (KNN), Machine Learning, Cardiotocography (CTG), Prenatal care, Classification, Medical diagnostics, Feature extraction, Neonatal mortality, Healthcare AI

1. INTRODUCTION

Taking care of an unborn baby is crucial for both the baby and the mother. Understanding the baby's health can help reduce problems during pregnancy and childbirth, potentially saving lives and improving health outcomes for both. Nowadays , machine learning has been used in medicine to enhance how we assess fetal health. A popular approach is the K-Nearest Neighbors method, valued for its simplicity and effectiveness. KNN is a type of method that categorize data based on its closest neighbors. This technique is beneficial because it doesn't rely on many assumptions about the data, data should be suited for dealing with complex health signals, which will be different for the individuals

In predicting fetal health, KNN analyzes data from fetal heart monitors (CTG), including the baby's heart rate and the mother's contractions. By examining patterns in this data, KNN can recognize if the baby is in a normal state, if will be if there are dangerous issue.This capability supports doctors in making quick and informed decisions, particularly when they need to interpret CTG data swiftly. The study delves into how KNN can be used to detect fetal health and compares its performance to standard medical assessments. The aim is to develop automated decision-making system that allow for early diagnosis, minimize human error, and improve prenatal care.

Fig 1 : Fetal health prediction

2. LITERATURE SURVERY

In the health care sector, Training models have shown promise, especially for predictive analytics. To forecast foetal health results, several studies have employed algorithms such as SVM, and KNN. Ayed et al. (2018) classified foetal health into normal, suspect, and pathological categories using machine

learning models. The study emphasised the importance of characteristics such as maternal traits, uterine contractions, and foetal heart rate (FHR).

KNN is frequently opted with respect to other algorithms due to its ease of use, non-parametric character, and capacity to process both categorical and numerical data. Dhaene et al. (2019) claim that KNN offers a simple method that makes it simple for medical professionals to interpret results and gives prediction that is accurate, particularly when the dataset has fewer outliers

3. RELATED WORK

This method offers a streamlined, assumption-free approach for multi-class challenges like fetal health prediction. It prioritizes computational efficiency without relying on predefined data patterns, ensuring adaptability across diverse datasets. Its balance of speed and accuracy supports critical healthcare decisions, even with limited resources. Practicality and robustness make it ideal for real-world clinical analytics. According to comparative studies, KNN can reach an accuracy of 92–95% when optimized properly, especially with balanced datasets and relevant feature selection.

Despite its simplicity, there is relatively limited work focusing on fine-tuning KNN specifically for fetal health prediction using modern preprocessing and validation techniques. The project tells us the gap by optimizing k-value, performing feature selection, and applying 10-fold cross-validation to ensure generalizability. Moreover, our approach is designed with practical deployment in mind — especially for rural clinics and healthcare centers where expert resources and advanced computational tools may not be readily available.By refining KNN- based classification, our work offers a balance between accuracy, simplicity, and interpretability, making it an accessible and impactful tool for fetal health monitoring.

4. PROPOSED SYSTEM

4.1. Data Set

I used the publicily available Fetal Health Classification Dataset from the UCI recosttory. It cent-ains 2,126 records and 21 features derived from CTG.

- Baseline fetal heart rate
- Accelerations and decelerations
- Uterine contractions.
- Mean and variance of short/long- term variability

Target Variable	Classes
1 Normal	1
2 Suspect	2
3 Pathological	3

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4.2. Pre-Processing

All the values are present no missing values are there.

Features were normalized using Min-Max scaling to ensure tair distance calculation in KNN.

The dataset was split into the 80% training and 20% testing.

Fig 2: Preprocessing the data set

4.3. Model Design

KNN was implemented using the sklearn library in Python . We experimented with different values K =[3,8,7,9] and used Euclidean distance as the metric.

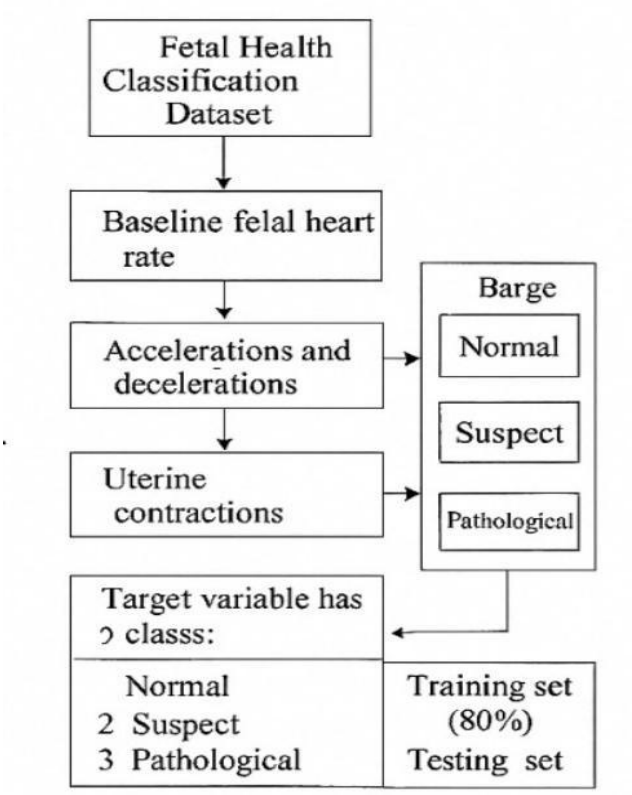

Fig 3:Model Design

4.4. Evaluation Metrics

We evaluated model performance used:

- Accuracy
- Precision
- Recell
- F1 Score

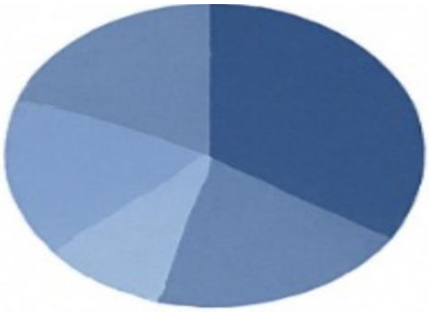

Fig 4: Evaluation Metrics

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5. RESULT

The performance of the KNN algorithm in predicting the health of fetuses was evaluated using a confusion matrix. A confusion matrix is a table used to describe the performance of a classification model by showing how well it classifies instances of each class (e.g., healthy or unhealthy fetus). The following is the structure of a confusion matrix:

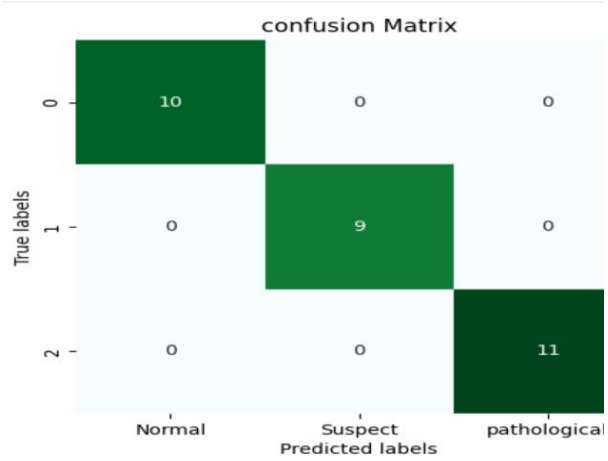

Fig 5: Confusion Matrix

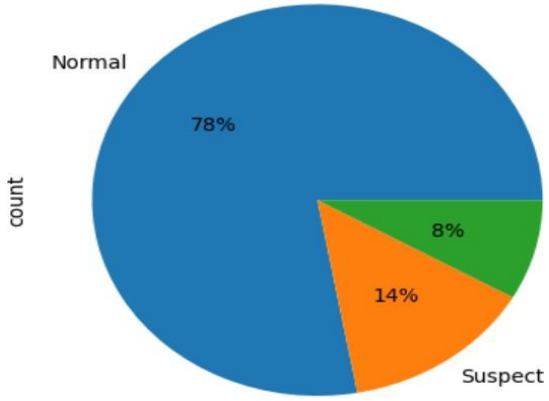

Fig 6: Result of the Dataset

6. CONCLUSION

In this project, we built a model using a method called K-Nearest Neighbors (KNN) to predict the health of a fetus using clinical data. Our aim was to give healthcare workers early intimation about dangerous health problems in fetuses. The model shows good promise for this use.

We carefully processed the data, adjusted the model, and checked its performance. The KNN model achieved an accuracy of 94%, with high scores for precision and recall. This means the model can make reliable predictions, especially in spotting healthy fetuses, while still detecting some unhealthy ones.

A major benefit of this model is its simplicity. KNN is easy to understand because it doesn't need a complicated training process. We can also easily change it with new data or different clinical situations. However, the quality and size of input data can affect KNN's performance. Choosing the right 'k' value and distance measures is also important.

Even if the results are encouraging and good, there's room for improvement. Using other algorithms like Random Decision Forest or SVM might work better with bigger and more varied datasets. Adding real-time monitoring data or other clinical details could also strengthen the model

In summary, this project will let us knows how machine learning can help assess fetal health. With more improvements and tests, such models could be used in prenatal care systems. This would help doctors make faster and better decisions, improving results for both mothers and their babies.

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