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Comparative Analysis of Machine Learning Classification Techniques for Neonatal Postprandial Hypoglycemia Symptoms Screening.

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Abstract: Neonatal postprandial hypoglycaemia occurs when blood sugar level (BSL) is too low to cause symptoms of impaired brain function among new-born babies. Machine learning algorithms such as Neural Networks, SVM, Naive Bayes, Decision Tree are widely used for detection and classification process of the disease. The Objective of this study is to design a model which shall compare the performance of three machine learning classification algorithms namely Decision Tree, SVM and Naive Bayes to detect diabetes at an early stage. The performances of all the three algorithms are evaluated on various measures such as accuracy, Recall, Precision and F-Measure. Classified instances are used to measure Accuracy. The results show that Naive Bayes outperforms with the highest accuracy of 86.40% comparatively other algorithms. This work forms basis for our next step which is utilizing Naïve Bayes Algorithm and Artificial Neural Network (ANN) for Type 1 Diabetes disease treatment.

Keywords: Machine learning, Naïve Bayes classification, Decision Tree, Support Vector machine, Neonatal postprandial hypoglycemia

Introduction

Diabetes is a chronic illness which occurs due to the failure of the pancreas. When the pancreas is not able to produce sufficient insulin or when the body cannot utilize the produced insulin, then there results to an increase in glucose level hence diabetes, Harding et al (2016). After taking food, it is broken down into glucose which enters the blood cells. The pancreas produces insulin which breaks down glucose into energy. If insulin is not produced or when it is not sufficient, then glucose is not broken down hence diabetes illness arises. Improper diagnosis of diabetes and control leads to serious health issues which may be blindness, Kidney failure, nerves failure or stroke and death.

There are three types of diabetes. Garten et al (2018) Type 1 Diabetes Mellitus (T1DM) which is also known as Juvenile diabetes. This type arises as a result of the pancreas stopping to generate insulin. This type of diabetes is more severe than the other types and is common among new-born babies or infants. To control the effects of this type of diabetes, a patient is injected many injections of insulin per day to stabilize the glucose levels. Type 2 Diabetes Mellitus (T2DM) is called adult diabetes and is common among adults, however it can develop at any stage of life. This type of diabetes originates from the body being resistance to insulin which later turns to pancreas failure or inability of the pancreas to produce sufficient insulin which can break down food.

Type 3 Diabetes Mellitus (T3DM) is known as gestational diabetes. It affects women during pregnancy. There are no symptoms to this type and occurs when the pancreas cannot

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produce enough insulin to support the required levels during pregnancy. Type 1 Diabetes Mellitus (T1DM) or Neonatal hypoglycaemia is a severe illness with no symptoms among new born babies. New-born babies require glucose for brain and organs development, Glucose consumption right from birth is high.

Ogurtsora et al (2017) clinicians have attached the failure of pancreas for new-borns to neonatal stress. The stress can be as a result of other infections, flu, prematurity, heart and lung disease. It takes a lot of tests and time to diagnose neonatal hypoglycaemia among babies and most of the time there are high chances of disease mis-diagnosis. Because of this, the infant may end up developing complications or death. There is need for an intelligent model to support clinicians and care givers in detecting early symptoms of neonatal hypoglycaemia among infants.

Problem statement

Controlling Neonatal postprandial hypoglycaemia through controlling blood glucose levels for babies has proven to be difficult especially for newborn babies. Neonatal period is the time duration between birth and the first twenty-eight days. a report by UNICEF, 2017 states that there are seven thousand (7,000) deaths per day on newborn babies within every seven days after birth. 39% of the deaths are reported in southern Asia and 38% Sub-Saharan Africa. The report shows that many neonatal deaths occur in mow and middle-income earning countries.

A report by WHO on neonatal mortality (2018) explains that Kenya records forty thousand (40,000) deaths annually of newborn babies within their first month after birth. Neonatal Hypoglycaemia has been highly reported in Africa with the rate of admission due to the infection raising up to 10%. Use of herbal medicine and delay in visiting hospital worsens the situation and to many children they end up having neural issues and mental disorders.

A simple treatment for the condition is oral intake of carbohydrate food by the diabetic infant. To monitor blood glucose for these babies, a doctor is required to draw a blood sample many times a day, also known as Capillary Blood Glucose Measurement (CBGM) which is very painful. New devices: - Continuous Glucose Monitoring (CGM) have been invented and are placed on a baby's body to read glucose levels without extracting blood samples. CGM devices have the capacity to obtain a baby's glucose level using interstitial fluid and not blood. The results produced by this device are in accurate. The measured glucose levels measured by CGM devices lag 8 to 10 minutes behind compared to blood glucose test kits. Detecting neonatal postprandial hypoglycaemia using the kits can be too late for a patient to take corrective actions; therefore, the need for the use of artificial intelligent methods in disease diagnosis and screening.

Objectives

i. To review the factors associated with neonatal postprandial hypoglycemia among infants
ii. To investigate the existing machine learning approaches, techniques and models for neonatal postprandial hypoglycemia screening
iii. To compare the performance of Decision Tree, Support Vector machine (SVM) and Naive Bayes Machine learning algorithms on classifying the symptoms of neonatal postprandial hypoglycemia.
iv. To present classification results of Decision Tree, Support Vector machine (SVM) and Naive Bayes Machine learning algorithms

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Literature Review

Perveen et al. (2016) compares two Decision tree classifiers, decision tree J48 and AdaBoost. AdaBoost classifiers out-performed J48 and produced more accurate results of disease diagnosis. Meng et al. (2013) compares the performance of decision tree, Logistic regression and Artificial Neural Network (ANN) to predict diabetes mellitus and pre-diabetic symptoms. Their included seven hundred and thirty-five patients who had diabetes and seven hundred and fifty-two without diabetes. To predict which patients had diabetes, ANN produced 78.97% accuracy, followed by decision tree with 77.87% then the logistic regression model had 73.50% accuracy predictions.

Sisodia, D. and Sisodia, D.S (2018) compared the results of diabetes symptoms screening results produced by Support Vector Machine. K-nearest Neighbors and Naïve Bayes classifier. The results of naïve Bayes Classifier had the highest accuracy prediction. There exists other research whose aim is not to compare the efficiency of the techniques but applying machine learning techniques to diabetes disease symptoms identification. Karakiotis et al. (2016), the authors developed a decision tree model to determine the number of women from the Pima Indian culture are suffering from diabetes. Their data set had 768 women and Their results showed that 500 of the females are non-diabetic (65.1%) and the rest (34.9%) are diabetic

Authors in Kovatcher et al. (2016), used a machine learning technique to predict next morning blood glucose levels from a person in fasting (FBG). Experiments were conducted among Four insulin treated diabetic patients for a period of three months. Patients were equipped with four gadgets, namely: A laptop which was used a food intake monitor, Blood glucose monitor and a metabolic rate monitor. The FBG was used to measure the fasting blood glucose level once a day. The patients were attached to the metabolic rate monitors to measure the rate at which the body burns calories Thornton et al. (2018). Calories simulating software was designed to calculate the calories of the food intake. The model provided a sample of meals for the patient to choose from and eat during breakfast, lunch and dinner. Data was collected and a decision tree technique was applied to predict blood glucose levels. Estimated FBG levels turned out inaccurate after eight weeks of data collection due to small blood glucose taken on daily basis.

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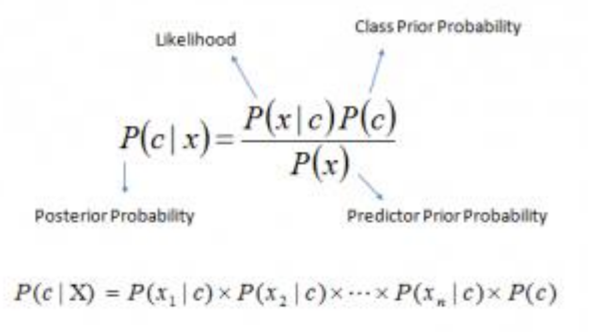
Methodology



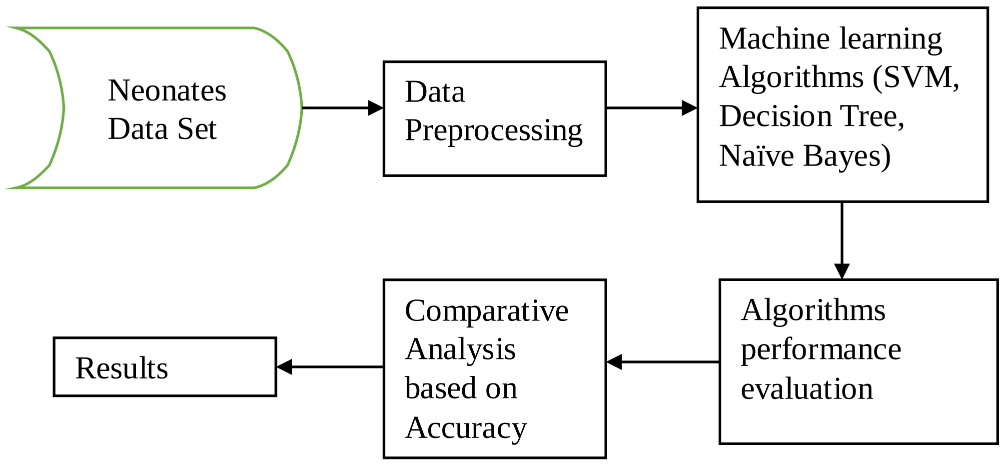


Figure 1: Machine learning technique performance analysis model

Naïve Bayes Classifier

Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature P(D) can be ignored as it is the same for both the terms. Naive Bayes model is easy to build and particularly useful for very large data sets. Along with simplicity, Naive Bayes is known to outperform even highly sophisticated classification methods. Bayes theorem provides a way of calculating posterior probability P(c|x) from P(c), P(x) and P(x|c). Look at the equation below:

i. $P(c|x)$ is the posterior probability of *class* (c, *target*) given *predictor* (x, *attributes*).

ii. $P(c)$ is the prior probability of *class*.

iii. $P(x|c)$ is the likelihood which is the probability of *predictor* given *class*.

iv. $P(x)$ is the prior probability of *predictor*.

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Table 1: Confusion matrix of Naïve Bayes Classification

	A	B
A Tested Positive	117	197
B Tested Negative	570	80

Decision Tree classification

It is a Supervised Machine Learning where the data is continuously split according to a certain parameter. A Decision Tree contains **Nodes** which are used to test for the value of a certain attribute, **Edges/ Branch** which ccorrespond to the outcome of a test and connect to the next node or leaf and leaf node which is a terminal node that predict the outcome (represent class labels or class distribution). Historical data was used and applied the decision rule of a decision tree to determine target classes. Weka simulation tool was used to run the experiments Iyer et al, (2017).

Table 2: Confusion matrix of Decision Tree Classification

	A	B
A Tested Positive	121	193
B Tested Negative	555	95

Support Vector Machine (SVM)

SVM algorithm aims to find the hyperplane in an N-dimensional space (N is the number of features) that distinctly classifies the data points. Hyperplanes are decision boundaries that help classify the data points. Data points falling on either side of the hyperplane can be attributed to different classes. Also, the dimension of the hyperplane depends upon the number of features. Sisodia et al (2018).

Table 3: Confusion matrix of SVM Classification

	A	B
A Tested Positive	281	0
B Tested Negative	648	0

Data Set

Historical data was provided by The Kenya Medical Research Institute (KEMRI) and Kenya Paediatric Association and Kenya. We collected data from the years 2017-2019. The data had to segments, babies born without diabetes and those with postprandial diabetes. The data file containing data of heathy babies was used a training data set and contained 7,450 instances. The file containing records of babies with diabetes had 4,578 instances and 3,500 was picked randomly as an independent test set.

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Table 4: Data Attribute description

Attribute	Abbreviation
1. Neonate Age	Na
2. Plasma Glucose Concentration	Gc
3. Birth Weight	Bw
4. Pulse Rate	Pr
5. Neonate Height	Nh
6. 2-Hour Serum Insulin (mu U/ml)	In

Table 5: Accuracy Measurement

Measurement	Meaning
1. Precision (P)	used to measure accuracy
2. Recall (R)	used to measure the classifiers completeness
3. Accuracy (A)	Determines the accuracy of the classifier in identifying instances
4. F Measure	This is the weighted average of precision and recall
5. Receiver Operating Curve (ROC)	Use to compare the importance of tests

Results

Table 6: Classified instances and algorithms performance

Total No. of instances	Algorithm	Correctly classified instances	Incorrectly classified instances
3,500	Naïve bayes	2,877	623
	Decision Tree	2,790	710
	SVM	2,200	1,300

Table 7: Comparative tabulation of algorithm performance

Algorithm	Precision	Recall	F-Measure	Accuracy%	ROC
Naïve bayes	0.767	0.770	0.763	86.40%	0.914
Decision Tree	0.741	0.734	0.732	75.30%	0.701
SVM	0.430	0.642	0.510	64.50%	0.510

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Figure 2: Classified instances

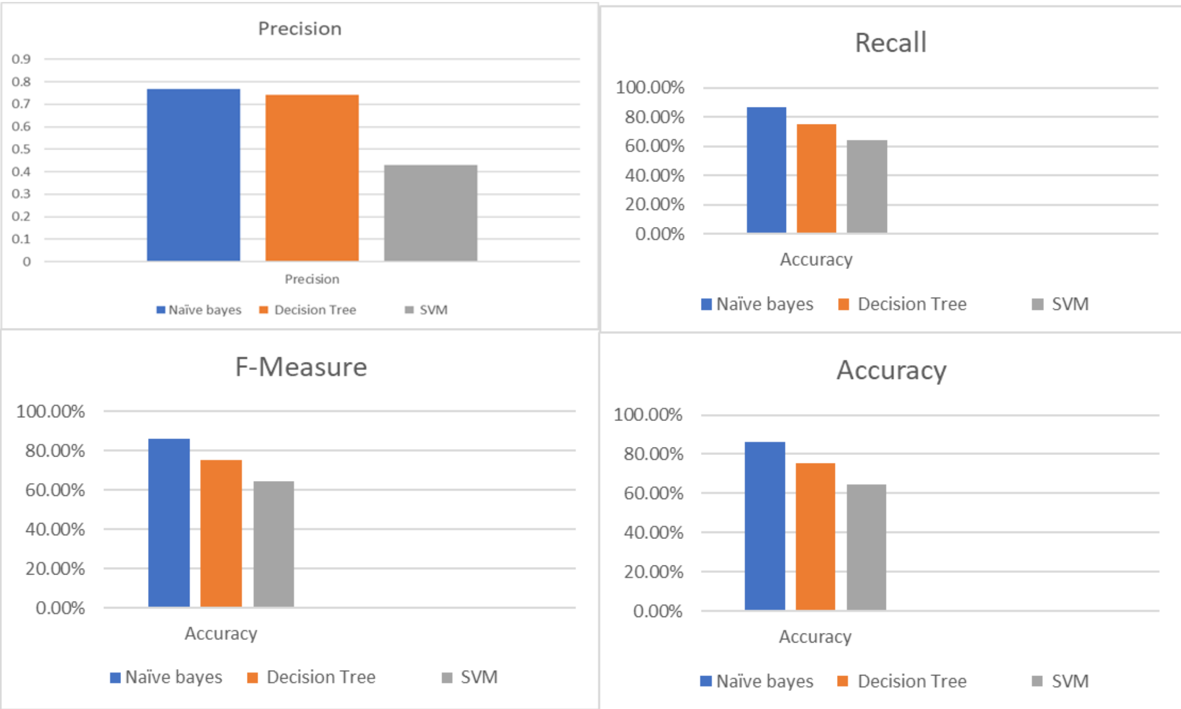

Figure 3: Algorithms performance on Various measurements

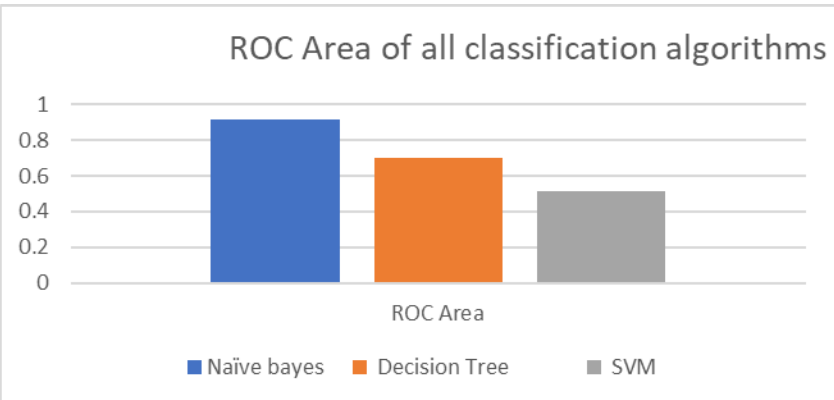

Figure 4: ROC Area for all algorithms

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Conclusion and Recommendations for future work

There is no cure for diabetes yet, but early symptoms diagnosis can lead to the right medication and recommendation of proper diet to the help control the disease and minimize deaths. The complexity of tracking glucose levels for babies has paved way to machine learning techniques as key technologies in providing solutions to empower both patients, care givers and clinicians in symptoms detection and blood glucose measurements. The techniques can be used to develop models which can be integrated within the medical systems and provide better support for the patients. Providing better systems for diabetes diagnosis and treatment will have a great help to patients, health care workers and ease the economic burden of the nation. In this paper, the performance of three machine learning classification algorithms are evaluated for neonatal hypoglycaemia symptoms prediction. Experiments were performed on data provided by The Kenya Medical Research Institute (KEMRI) and Kenya Paediatric Association. Naïve Bayes algorithm happen to have the highest accuracy of prediction of 86.40% . This work can be extended and improved in future by examining the Deep learning algorithms for the disease symptoms screening and treatment.

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