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ISSN 1462 2815

ANALYSIS OF IoT AND MACHINE LEARNING FOR COMMUNITY HEALTH IMPROVEMENT REAL-TIME APPLICATION FOR RURAL DEVELOPMENT

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DOI: 10.5281/zenodo.11615324

Abstract

This research aims at enhancing the methodologies and procedures of a community health problem-solving approach through an integration with newly developed technologies using devices produced by Internet of Things (IoT). The objective of this research is to develop and test machine learning models for predicting patient clinical outcomes based on temperature, pressure, blood glucose and heart rate sensor data. In this research four machine learning models used Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree (DT) and Naive Bayes (NB) on a dataset of sensor readings from 10 patients over time. A set of 2100 readings are divided into training and testing sets, with a ratio that utilizes 70% of the data for training and the remaining 30% to testing. The performance of the models in terms of predicting patient health outcomes is evaluated using a number of metrics including accuracy, precision, recall and F1-score. A comparison of sensitivity, specificity accuracy and AUC between the ANN approach (97.6% in average), SVM model at 93.4%, DT with the lowest value at 90.25% and NB (mean: 88.56%). For the active surveillance of rural areas, an ANN model excelling in capturing complex data patterns have been considered as the best suited with enhanced accuracy and robustness.

Keywords: IoT, Deep Learning, Healthcare, Rural Development, Sensor Data.

1. INTRODUCTION

Recent technology enhancements have driven significant transformation in the delivery on healthcare, presenting new opportunities for increasingly improved patient and community health. [1], [2]. Nonetheless, even as technology progresses, such advancements are of little help for under-served rural areas around the globe where resources and infrastructure continue to lag behind. This is where IoT enabled deep learning means can be fruitful in bridging the gap of health care service rendered to remote people. IoT sensors that continuously collect health readings, and artificial neural networks to process real-time data analyses will enable healthcare providers to have better insights into their patient's wellbeing, and take corrective actions as soon as necessary — providing personalized care. [3], [4].

Innovative solutions such as remote patient monitoring, chronic disease management, and personalized healthcare delivery are being implemented using IoT in the field of health. IoT integrates sensors and devices into healthcare systems, allowing real-time monitoring of patient health metrics (vital signs, activity levels, medication adherence) [5]–[7]. This information can be relayed to healthcare organizations and used in real-time to provide actionable insights that enable timely interventions and proactively manage patients with chronic diseases.

These have significant and relevance in rural development settings where access to healthcare services is expected to be scattered, as IoT-based treatment helps bettering the health care accessibility over-coming geographic constraints. IoT-enabled remote patient monitoring provides an opportunity to help healthcare providers remotely monitor the health status of patients in real-time and intervene when necessary, resulting in a reduced number of visits for follow-up and better patient outcomes [8], [9].

One of the most significant developments in healthcare has been seen in AI and deep learning, which are technologies that can be used to efficiently analyze large datasets, as well as correlate multiple variables with each other. Deep learning algorithms can be trained on sensor data for pattern recognition, predictive analytics of healthcare outcomes and detecting anomalies in the context of IoT enabled healthcare [7], [10], [11]. They can learn from vast amounts of data and predict the future with a high level of accuracy while enabling care providers to make better informed decisions in their daily practice, leading to more personalized healthcare.

Over the last few years, numerous studies have shown that deep learning models can perform as good of a job as humans in healthcare tasks such as disease diagnosis, treatment planning and prognosis prediction. One of these is deep learning algorithms that analyze medical images (X-rays, MRI) and find the diseases with a high level of accuracy. Furthermore, machine learning models and deep learning have been used to predict outcomes of patients in electronic health records (EHRs) and provide personalized treatment plans [12], [13].

In rural healthcare settings with limited access to specialized medical expertise, deep learning algorithms could assist local health providers in decision support and diagnostics. Utilizing deep learning models and sensor data captured by IoT devices working in concert can analyze early onset symptoms of health deterioration, predict the progression of a disease state, and recommend the ideal type of intervention. To the extent that it may enable providers in rural areas to provide high quality care and enhance patient outcomes, even when resources are limited [14], [15].

While IoT and deep learning have the potential of being highly useful in rural healthcare, many problems still exist. Privacy and security issues must be addressed in the collection, transmission, storage for patient data to meet both regulatory mandates and patient confidentiality. Moreover, data interoperability and its inconsistency among various IoT devices and systems can act as a constraint in the sharing of data across by implementation with each other which makes it difficult for enabling optimal use-cases within the system via Iot healthcare solutions [16], [17].

This research examines how emerging trends IoT and machine learning can be used for better health improvement in rural development areas. The main goal is to build machine learning models which can predict patient health outcomes using sensor data from different sources such as temperature, pressure, blood glucose and heartrate sensors. Leveraging sensors for analyzing patient-generated health data, these models are targeted toward empowering healthcare providers with insights into the state of patient health and early detection of potential health problems as well as proactively managing chronic diseases.

2. METHODOLOGY

The IoT system in this research uses an assortment of sensors to collect key health indicators. The patient body temperature, vital for fever and infection detection, is monitored by the Temperature Sensor. The first is a Pressure sensor, which tells you blood pressure and gives information about your heart health. The blood glucose sensor is immensely important to those with diabetes because they tag the patient's blood sugar levels. The heartbeat sensor Revolutionized wearable technology to detect arrhythmias and other heart conditions. Those sensors collect data every second, providing a real-time snapshot of the patient's health status. The methodology of the research are shown in figure 1.

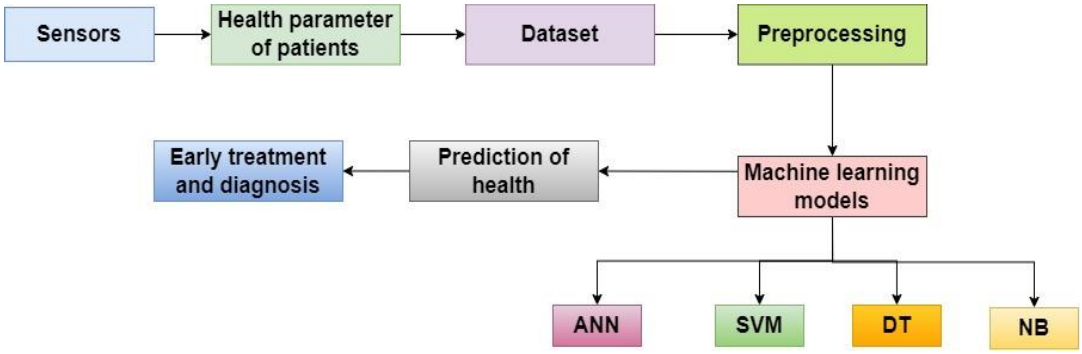

Figure 1: Working of the proposed research

IoT system can quickly pass the data to health service holders, which is one of its prime merits. This is very helpful to rural places who find it hard to get access to medical facilities. Patients' sensor data are transmitted to hospitals using secure and trusted communication networks that doctors can anytime view. Doctors may utilise this real-time data to monitor their patients from a distance, helping them make educated decisions and intervening with medical advice or actions as required. This system not just links patients and healthcare providers but also enhancements the effectiveness of delivering rural healthcare besides.

Various machine learning models are trained on sensor data to enhance the predictive capabilities of the IoT system further. In this study the models are Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT) and Naive Bayes (NB). The trends and patterns seen in the sensor analytics can be used to make a very accurate prediction about what will happen with that particular patient from health wise standpoint — through these models. The approach recognizes that a different pattern of health data may signal the need for medication tuning (such as an increase or decrease in blood sugar levels) than reveal other issues, like those involving the heart (represented by fluctuations in heart rate). Based on these ML models, the solution provides essential patterns for predictions and other features contribute to effective predictive management in healthcare.

Every ML model used in this study has its own set of capabilities, which are detailed for detecting and predicting health outcomes. As the ANN can model complex relationships in data, it is highly capable of capturing non-linear patterns that may exist in sensor readings. SVM is a classification algorithm that efficiently classifies health states, especially dealing with high-dimensional data. Because of its tree-like structure, decision-making processes can be easily understood by healthcare professionals to interpret the predictions and DT offers an intuitive understanding.

Since NB is a simple algorithm, it fares well in scenarios where the outcome is probabilistic and you need to make sure your predictions are quite dependable. The integration of these models creates a scalable and resilient health forecasting system that supports numerous diseases and clinic needs.

Rural healthcare could see tremendous benefits by bringing such an IoT and ML system into the mix. The system offers doctors an opportunity to confidently offer more proactive care by using real-time health monitoring and accurate predictions, even when they are miles away. This is especially critical in quite a few rural areas with no proper infrastructure for healthcare and patients being forced to cover long distances for any facility. The system also lighten the load on hospitals as it decreases operational footprints, cutting down the amount of in-person visits required and making more efficient use of medical resources.

3. DATA TRANSMISSION OF THE PROPOSED SYSTEM

The rural healthcare-improvement IoT system, where the sensors communicate with an Arduino microcontroller. One man, one monitor: each sensor is used to keep track of a certain parameter in patients. The temperature sensor tracks the patient’s body temp for important feedback in case of any fever or infection. Blood pressure is a critical cardiovascular health biomarker, recorded by the pressure sensor. With the blood glucose sensor, you can track glucose levels in your blood and thus manage diabetes well. Heart rate is key for atrial fibrillation detection and some other cardiovascular heart disease, which the heartbeat sensor monitors.

These sensors are connected to an Arduino microcontroller unit, which acts as the primary data collection and processing hub. Each of the sensors forwards its readings to the Arduino, which then processes them in real time. This info, then gets sent from microcontroller to a WiFi module via GPIO (es). This Unit will handle the Wireless Connection and Sensors Readings Transferring to the Hospital Cloud Server.

Data sent to the WiFi module is transmitted over the internet back to a server in their hospital. This server belongs to the secure cloud system created to store and coordinate patient health data. Cloud technology ensures the data can be accessed from virtually anywhere, thus making it less cumbersome and more flexible for health care providers. Sensor Data is securely stored on the server and can now be accessed by authorized personnel.

And the server can provide access to doctors (authenticated) for quite reasonable reasons and they can see patient health data in real time. In this way, the healthcare providers can monitor the conditions to their patients remotely and not calling them for hospital visits more often. Token-based secure authentication ensures that the data about patient is only available for proper medical experts and is kept private well by advanced security.

4. MACHINE LEARNING MODELS

4.1 Artificial Neural Network

Artificial Neural Networks (ANN): An important part of this research, used for the analysis of sensor data and to predict patient health outcomes. Some types of ANNs resemble the brain's structure and functioning, which allows them to learn sophisticated patterns between data. The ANN models trained in this study are built

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using past sensor data obtained from patients, such as temperature, blood pressure, blood glucose level measurements and heart rate readings. ANN is assembled by layers of interconnected neurons: an input layer, a single or several hidden layers, and the output layer. Every neuron receives input data, processes it and passes the output to the next layer. The network modifies the strengths of connections between neurons (synaptic weights) during training based on the error in predicted output and actual outcome through backpropagation. The network trains itself through this iterating process, continuously refining its predictions until it reaches an acceptable level of accuracy.

This is even more useful in the rural healthcare scenario, where ANN can model non-linear and complex relationships. An example here being that the model can be trained to pick up on slight patterns in a patient's blood glucose levels (i.e. indicating an upcoming hypo). The system will alert healthcare providers to take corrective action by predicting these events accurately so that patient outcomes can be improved. ANNs, in addition, can combine several physiological variables together to provide a top-level view about the health of a patient.

4.2 Support Vector Machine

In this context, Support Vector Machines (SVM) are pivotal to the data for reliable patient type detection in healthcare which make categorization in a problem requiring classification more robust. SVM is a binary classification algorithm from the supervised learning kind and works really well in high dimensional spaces. This study trains SVM models on sensor data to distinguish between different health states of the patients (e. g. normal and» abnormal readings).

The central principle of SVM is to find the hyperplane that maximally separates the data into different classes. It is a hyperplane that serves as a decision boundary where are objects of data point which lies close to the plane, it known as support vectors. The model then uses these support vectors to create a boundary which classifies everything with the highest accuracy and makes it as robust as possible. SVM minimizes the risk of misclassification and thus improves the model generalization ability by maximizing the margin. In healthcare use case, you could take readings from a sensor and fit it into a bucket easily - normal blood pressure versus hypertension or stable glucose levels versus diabetic conditions using SVM. One simple example is using an SVM model in order to differentiate blood pressure data that are normal range from those which might be indicative of hypertension. This classification speeds up the recognition of patients requiring urgent help or medical intervention with doctors.

4.3 Decision Tree

This research also uses decision trees (DT) since it is an effective machine learning model that can be used to analyse sensor data and predict health outcome of the patient. Decision Trees are intuitive and interpretable but yet very powerful tools in modelling decision-making processes. They work by recursively splitting data into subsets based on feature values, creating a tree-like structure (where each node is a decision rule and the leaf nodes are outcomes). The DT algorithm works by finding the best feature for splitting data at each node through Gini impurity or information gain etc. These criteria evaluate how well the data is distributed using a split. This process continues until a maximum depth is met or the subsets at each level of all nodes are homogenous enough. Those decision rules from the root to a leaf node can then be used to make predictions with, resulting in a tree.

Decision Trees provide a way to understand and utilize sensor data in rural healthcare. Example: A Decision Tree could learn how to predict the probability of a diabetic complication if blood glucose, and other readings were considered. It allows for healthcare providers to follow the decision path with ease and further understand why a certain high-risk prediction has been made. The main strength of Decision trees is that thy provide a framework for easy interpretability this allows medical professionals to get the why behind every prediction, helping them trust and act upon the model's recommendations. Moreover, DTs can process numerical as well as categorical values and hence they are very general purpose for analyzing any kind of sensor data.

4.4 Navie Bayes

Another important machine learning model, which is used in the present study to predict patient health outcomes based on sensor data, is Naive Bayes (NB). Naive Bayes is a probabilistic classifier that uses the same principle as above i.e. Bayesian theorem for prediction, and it assumes no feature in train data set is dependent on each other which causes the model naive hence called as Naive Bayes. Although it is a naive approach to classification, Naive Bayes has been found quite powerful in practice for various applications that involve classifying text as the dimensionality of the data is high. The data is the sensor data, i.e. temperature, blood pressure and blood sugar levels reading and heart rate readings on which Naive Bayes model are trained. With the sensor reading, it outputs the probability that a patient has of being in some health category. For example, based on the temperature’s sensor reads and blood pressure sensor reads, we can predict if a patient is likely to have fever or hypertension.

The Great Strength of Naive Bayes algorithms is simplicity and computational efficiency in large data categories. It deals with high volumes of data quite well, and it does not over-train much even on small training datasets. It is the reason why it works good in real-time health monitoring systems where we need faster and efficient predictions. Furthermore, Naive Bayes is less sensitive to features irrelevant to the class or noisy data coming from sensors. On a practical level, we can use Naive Bayes to enter the minds of physicians and understand how they are thinking about patient outcomes probabilistically. And again, like in the previous case — the probability of patient normalization blood glucose sensor readings (a rising trend). Healthcare providers can then use these risk levels to decide on the appropriate interventions.

5. DATASET AND PREPROCESSING

This study collects information from the above implanted sensors to keep track of patients' diseases. That included temperature, pressure, blood glucose and heartbeat sensors to take real-time readings from patients. The data collected was from 10 patients, obtaining a final set of 2100 individual sensor readings to train and test the machine learning model. All these reads provide a solid base for training and testing of machine learning models. The data set has been divided into two groups, 70% of the observations (1470 readings) are used to fit/train the models. Such training data helps the models understand different patterns and relationships in sensor readings. The 30%, or 630 readings, are termed to be equity for testing.

Collecting raw data from patients sensors deployed for smart home. This is usually time-series data, which generates a lot of timestamp readings. First clean the data, remove missing values, outliers and sort any format inconsistency. The data is likely

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to contain missing values for problems such as sensor malfunctions or connectivity issues. Techniques like interpolation or imputation are used to fill these gaps with estimated values calculated using nearby data points. Identify and Deal With Outliers, which are values that differ substantially from the rest of the data. These might indicate sensor errors or unusual health conditions that warrant further investigation. Outliers are detected using statistical methods (z-score or IQR for example) for instance. Outliers are also removed or adjusted if outliers turn out to bias the training a little bit depending on their cause, thus creating clean and unbiased data for machine learning models.

After cleaning the data, normalization and scaling are used to normalize sensor readings. Sensors from different sources measure the data at different scales, for example blood glucose level may be in the scale of 70–180mg/dl whereas hearing rate will have a range between 60-100 bpm. It leads normalization of these different scaled entities to a common scale generally 0–1 so that there is no feature which will dominate others in training for model due to their scales. For that, usually, methods like Min-Max scaling or z-score normalization are more often used.

IFs-processes sensor readings to convert them into health-related features, as raw sensory data cannot efficiently represent the actual health conditions. One example of this could be using average heart rate, detailed heart-rate variability, or % change in heartrate over time instead of raw heart rate readings. It extracts features corresponding to results of laboratory tests like fasting glucose, postprandial glucose and insulin as well as glucose variability for blood glucoses levels.

Extraction is followed by feature selection, which seek to discover the predictive features of health outcomes. Dimensionality reduction to boost model performance and interpretability Feature selection is the process of selecting a subset of most relevant features from possibly many irrelevant ones, and methods like correlation analysis, PCA or RFE are used for this purpose.

A 2100 reading dataset from 10 patients is divided into windows to capture temporal patterns. Every window could be a different time period, for example an hourly or daily value - these can provide insights into short term trends and long-term patterns. These groups are classified according to the disease or thresholds specified for health conditions. For instance, blood sugar readings over a set level could be labelled hyperglycemia and heart rate measurements in one of a specific range might be considered normal or bad.

The preprocessed and tagged data is separated into train data and test data in order to measure the performance of machine learning models reliably. This research employs 70% of the data (1470 readings) for training the models. Data on which model gets trained is called training set that helps in learning the patterns and relationships inside this data. The final 630 readings, or other 30%, are offered out for testing. The testing set is used only to validate the model predictions before going live or using it for a real-world problem.

If the data is imbalanced (not equally balanced among all health conditions), use techniques like oversampling, under sampling or synthetic data generation (e.g., SMOTE) to balance the classes. This step is important to avoid the models being biased with majority class and make them able to accurately predict minority health conditions.

6. RESULT AND DISCUSSION

The machine learning models were trained on the pre-processed sensor data and evaluated for their performance using the testing dataset. The result is shown in figure 2. The performance of all models was evaluated in terms of the calculation if its weighted sensitivity, specificity by responses and PPV-1 score to predict patient at severe health risk. The recommended type, the Artificial Neural Network (ANN) model yielded a 97.6 accuracy in response prediction. This is actually quite accurate since ANN could capture complicated non-linear relationships between data, rendering it to be pretty efficient in analyzing the multidimensional patterns of health sensor readings.

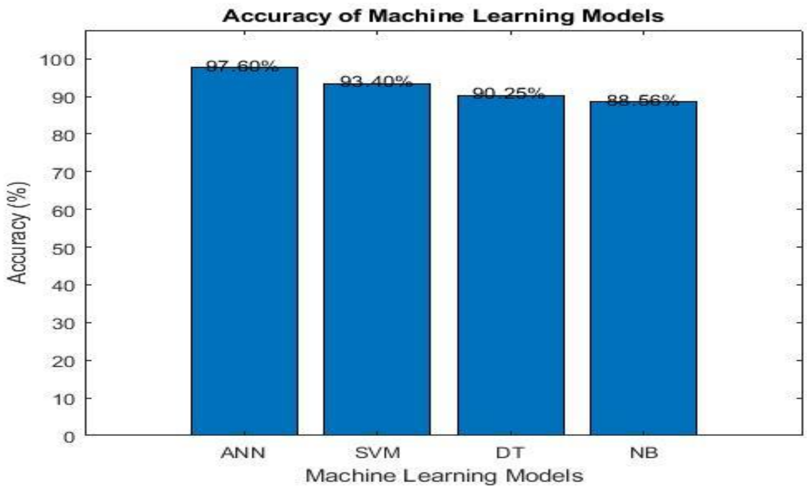

Figure 2: Accuracy of each model

The Support Vector Machine (SVM) model comes out as being the second best, and achieves an accuracy of 93.4% SVM performs well in high dimensional spaces and is able to find an optimal hyperplane that discriminates two different health states. This makes SVM optimal for tasks in which identifying the decision boundary is a major factor, such as image classification jobs. The Decision Tree (DT) model had an accuracy of 90.25%. The decision tree is esteemed since it gives clear and simple to pursue rules while likewise looking similar to a human-readable rule. Compared with ANN and SVM, the accuracy of DTs is slightly lower, but it provides some directly visible factors for research, which is meaningful in practical application because clinical doctors can easily understand part mechanism that model predicts. The Naive Bayes (NB) model which was the one of simpler form out of these four models have better accuracy achieved at 88.56% The success of Naive Bayes is mainly because it uses a probabilistic approach and can handle high-dimensional data efficiently. While not as accurate, NB is still a worthwhile model because it is the computationally most efficient ML estimator and outputs by nature probabilities in an interpretable manner.

The performance of each machine learning model was evaluated using several key metrics, including accuracy, precision, recall, and F1-score, to provide a comprehensive assessment of their effectiveness in predicting patient health outcomes. The results are shown in figure 3.The Artificial Neural Network (ANN) model demonstrated exceptional performance, achieving an accuracy of 97.6%. A high accuracy level, thus evidencing that the ANN model is quite good at identifying as well as predicting which type of health outcome correctly. The ANN also had 98.0% precision, meaning that it does not falsely claim a patient to be infected; and the number of opportunities for this is low due to an imbalanced training set in which attached patients are rare. Moreover, the ANN scored a recall to 97.5%, which means it could identify nearly all (not the false positives) of those that had a health condition F1 score that gives the best of both precision and recall was 97.7% hence we can conclude that this model is quite reliable and robust in overall.

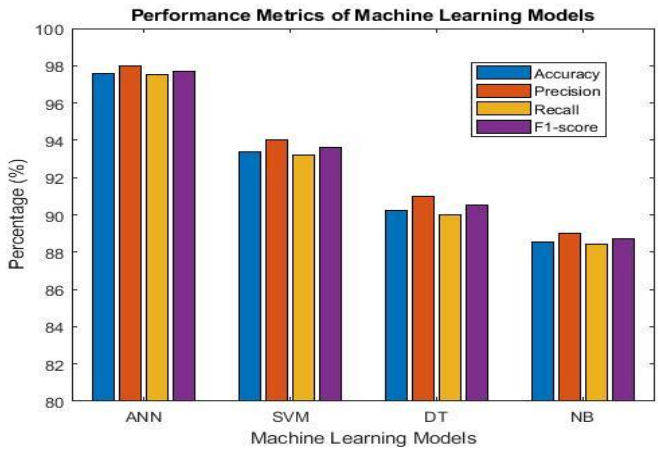

Figure 3: Performance of each model

Again, the Support Vector Machine (SVM) provided a strong performance with an accuracy of 93.4% This suggests that SVM is resilient in separating well-being outcomes successfully. This means it can make the “truest” positive predictions with recall at 93.2%. The F1-score (93.6%) confirms that SVM provides proper trade-off between precision and recall, which means SVM is a good predictive model for health condition.

Although Decision Tree (DT) model is less accurate than ANN and SVM, this model has displayed a good performance of an accuracy of 90.25%. The DT model has 91.0% precision; this means the percentage of positive predictions are correct. There was a 90.0% recall, demonstrating that we could reliably find many of the true positive examples. The balanced performance of the Decision Tree model is also visible in its F1-score 90.5% being by large meanwhile and significant advantages for decision making over opaque models are interpretability, which helps keep both feet firmly on the ground when it comes to medical applications.

The simplest one, the Naive Bayes (NB) showed an accuracy of 88.56%. This result shows the precision of NB model was 89.0% which means it can make correct positive predictions three out of ten times. This meant it had a recall of 88.4%, indicating that it was able to identify many true positive cases the high F1-score of 88.7% by Naive Bayes tells that it has a good balance between precision and recall. It is still a very useful model and good at many classification problems, especially for real-time applications where we have limited computational resources.

Confusion Matrices offer an insightful look at how well the machine learning models predict a patient's health outcome, in comparison to the testing dataset. The result of confusion matrices are shown in figure 4. Thus, each matrix provides a summary of the actual and predicted classifications in terms of true positives (TP), true negatives (TN), false positives (FP) as well as false negatives (FN). For the Artificial Neural Network (ANN), the matrix represent 308 true negative predictions and 315 true positive predictions which means that our model not only correctly predicted as

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absence of health conditions but also presence of them in a considerable instances. Nonetheless, the model made 7 false positive predictions and 10 false negative predictions hinting at some misclassifications of when a health condition is present or not.

Support Vector Machine (SVM) also gave a great prediction with 287 true negative and 295 true positive predictions. The GBM model followed with fewer amounts of false positives and negative predictions than KNN, yet slightly more misclassifications in comparison to the ANN auxiliary. The Decision Tree (DT) model has also performance well and could correctly predict 290 samples as negative (true negative: TN) and 284 out of these were truly positive (true positive: tp). Nevertheless, the rate of misclassifications was slightly increased in contrast to both ANN and SVM models: 25 false positive predictions versus 27 in ANN model, as well as 31 false negative predictions against all points being correctly classified by these two others.

Finally, the NB model even though simpler did give 273 true negative predictions and 274 true positive cases with decent performance. Nevertheless, 42 false positives and 41 false negatives were predicted with the model indicating in fact a bit more misclassifications comparatively to the other models.

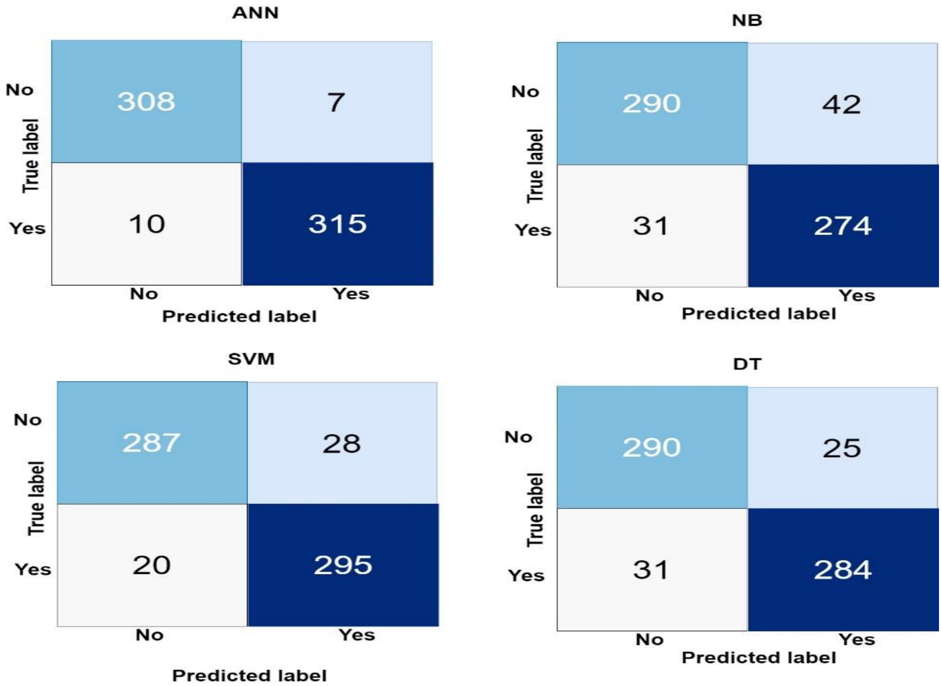

Figure 4: Confusion matrices of each model

CONCLUSION

The research was able to develop and validate four machine learning models; Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree (DT) and Naive Bayes (NB) using sensor data from temperature, pressure, blood glucose and heart rate sensors. The performance evaluation showed that almost all models have significant performance and accuracy to predict patient health status. Among different models, ANN gave the highest accuracy of 97.6% The complexity and sophistication required for handling/processing complex relationships within data for predicting accurately is what makes it even effective using this technique to monitor the healthcare. And the SVM model is not very far behind, showing good classification accuracy of 93.4%, which demonstrates its ability to perform well even in high-dimensional space data streams depending on how complex it is Options Resolver While the Dt model had plainly good accuracy that was just a notch lower at 90.25%, it did provide us with very useful insights what going on inside its interpretable process of decision making. Although it was a simple model, the NB model already showed 88.56% accuracy, and could be used for real-time supports.

Overall, the ANN model showed excellent performance in predicting accurate patient health outcomes among all models. Because of its high accuracy and the ability to handle complex types of data patterns, it could be seen as useful in rural healthcare monitoring. But the choice to ship one model and. another will depend on various factors, such as computational resources, interpretability, and constraints of a specific application. The current shows how IoT and Deep Learning technologies could drive a new era in healthcare delivery especially for persons living in rural underprivileged communities by predicting health conditions on time with optimal accuracy thereby improving patient outcomes.

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