Implementation of Machine Learning based E-Healthcare in an Internet of Things Environment

Dr.Aruna.M[1], Salmoli Chandra[2], R. Sudharsanan[3*], Viswanathan Ramasamy[4], KDV Prasad[5], Rishu Kumar[6]

[1]Associate Professor, Department of Electrical and Electronics Engineering, Nitte Meenakshi Institute of Technology, Bangalore, Karnataka, India.
[2]Department of Data Science, B. P. Poddar Institute of Management and Technology, Kolkata, West Bengal, India.
[3*]Assistant Professor, Department of Information Technology, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, India.
[4]Professor, Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Guntur, AP, India.
[5]Assistant Professor (Research), Symbiosis Institute of Business Management, Hyderabad, Symbiosis International (Deemed University), Pune, India.
[6]Computer Science and Engineering, Institute of Technical Education and Research, SOA, Bhubaneswar, Odisha, India.

Abstract

Due to the availability of vast amounts of data related to various diseases, a heterogeneous environment, structured and unstructured data, and people's awareness of their individual health status, healthcare is an emerging field of study. Smart devices, fitness bands, sensors, and healthcare apps all play a vital role in the field of healthcare, as do technological advancements. The invention of these devices advanced medical care to the next level. Consequently, everyone is concerned about their health status and potential outcomes. Therefore, the most important aspect of the healthcare industry is the accurate analysis of health data and healthcare services. On the other hand, machine learning is a well-known and extensively utilised method for analysing and predicting healthcare data. The purpose of machine learning is to make accurate decisions and diagnose diseases earlier. Additionally, the primary objective of this work is to address accurate and timely disease diagnosis. This study examines the stroke dataset for more rapid and precise diagnosis. Numerous ML techniques have been reported in the literature, but accuracy is the primary concern, particularly with healthcare datasets.

Keywords: Healthcare, Machine Learning, Fitness, Data, IoT and K-means.

1. INTRODUCTION

Technology improvements have allowed for the collection of massive amounts of data, particularly in the biological and healthcare industries. Generally speaking, the acquired data is of an unstructured type and may be represented visually, aurally, textually, etc. Therefore, it is a challenging job to extract useful information from the massive quantity of data collected. It is also noted that early identification of sickness greatly reduces the danger to human life[1]. Unfortunately, information that is useful for making judgements cannot be mined effectively. On the other hand, data mining is a relatively new discipline that aims to mine vast datasets for previously undiscovered patterns or information. Depending on the facts at hand, the mined knowledge may inform a variety of management choices. In addition, the data and patterns that are mined may be divided into two groups: (i) legitimate patterns, and (ii) invalid patterns. Machine learning is a branch of data mining that explores various learning strategies, including supervised, semi-supervised, and unsupervised approaches. The goal of machine learning is to automate the process of information extraction in terms of prediction and classification, and several statistical (DT, NB, Regression) and meta-heuristic (GA, PSO, ACO) methods have been associated with machine learning to accomplish this goal. Many studies have looked at the potential of machine learning for accurate illness prediction. However, rapid and precise illness detection is an essential need in the healthcare sector[2]. Healthcare data analysis in terms of illness phases, decision making, prognosis, and maintenance of electronic health records is therefore a job very suited for machine learning systems. More precise diagnostic outcomes are anticipated from the use of machine learning algorithms, which are thought to be able to operate with both organised and unstructured data[3]. It has also been noted that effective healthcare data analysis techniques based on ontologies and multi-agent systems have been created. Multiple agents work together in a multi-agent system to sift through data for useful information and patterns. Meanwhile, the goal of an ontology-based system is to facilitate the extraction of semantic rules from data. The goal of developing remote monitoring systems is to give distant users with access to health facilities. The material also mentions some kind of smart internet healthcare system.

2. MACHINE LEARNING IN E-HEALTHCARE

Machine learning is a hot topic in the field of electronic healthcare and has far-reaching implications for society. Designing and developing an efficient and successful e-healthcare system is challenging without the use of machine learning. Machine learning's primary use is the analysis of diverse or homogeneous healthcare data obtained from a variety of sources. Building an ML algorithm that can handle both types of data well is a challenging problem. A huge number of healthcare equipment, such as smart watches, fitness bands, and sensors, have been invented up to this point, and the bulk of the population uses these items to keep tabs on their own health[4]. Individual health data is also gathered by these devices, and a machine learning algorithm is built in to help identify any out-of-the-ordinary patterns or behaviours. These gadgets are set to send an alert to the user if they detect something out of the ordinary. Thus, ML is a promising instrument that might lessen the financial burden of medical equipment and better explain the doctor-patient dynamic. Machine learning and large amounts of data have proven useful in the healthcare industry, assisting with anything from the creation of individualised treatment plans and prescriptions to patient follow-up and reminders. X-rays, MRI scans, CT scans, electrocardiograms, and other medical image and signal data are all produced and stored online by the healthcare industry[5]. It is countered that the healthcare sector works with both types of data, including signal data like ECGs and images like MRIs. Structured data is easier to examine and organise than unstructured data. Reason being: there is no standard format for unstructured data. Patient heights, weights, and temperatures may all be expressed as structured data, as can more general complaints like a headache or stomachache. Different kinds of notes, reports, discharge summaries, pictures, and videos are all examples of unstructured data. Unstructured data, such as conversations between patients and doctors, may be highly individualised and skewed in a variety of ways, making them difficult to classify and measure[6]. Let's say two people are sick with a cold and it turns out that they have the same strain. However, as each patient and clinician has their own unique history and perspective, the dialogue and information may change. In the medical field, it has been observed that 80% of data is unstructured while 20% is structured. As a result, the data's characteristics have a significant bearing on how well ML classifiers function. It is taken for granted that all data kinds and data structures can be handled effectively and efficiently by today's ML classifiers. These algorithms also built a connection between raw data and other types of unstructured data. While a variety of artificial strategies exist for dealing with structured data, there is a dearth of methods for dealing with unstructured data in the current landscape[7]. Nonetheless, ML classifiers and approaches manage both datasets well. Accurate prognosis and diagnosis have inspired the development of several expert systems, diagnostic systems, and ontology systems. It has also been observed that the use of machine learning in the field of diagnosis yields answers that are close to ideal, or that machine learning diagnostic aids clinicians in making pertinent decisions about the identification of diseases. ML's several applications include patient risk assessment, pharmaceutical outcome prediction, drug and illness prediction, and healthcare cost reduction[8]. It is also noted that the bulk of the populace may not be able to afford the therapy due to its expensive price. Machine learning has been used by a growing number of businesses and researchers to improve the accuracy with which organised and unstructured data may be used to predict medical outcomes. Only 5% of patients pay 50% of healthcare costs, which is a significant disparity. However, machine learning demonstrates its efficacy in accurate illness diagnosis and prediction.

3. LITERATURE SURVEY

The literature review on prognosis and diagnosis is described here. Algorithms for machine learning, meta-heuristic algorithms, and AI approaches to medical informatics are all covered in detail.

In [9], a machine learning approach is created to enhance the precision of coronary artery disease diagnosis. The suggested ML strategy, N2Gentic Optimizer, combines particle swarm optimisation with genetic algorithm. In addition, a normalisation technique is used for pre-processing the data. The aforementioned combination is actually used twice to provide the highest degree of precision. On the Z-Alizadeh Sani dataset, the efficiency of the N2Genetic optimizer is assessed. The results shown that the suggested N2Genetic -nuSVM achieves a diagnosis accuracy of above 93%. Patients with cardiac arrhythmia might be hard to categorise since their symptoms are so interchangeable with those of other disorders. Therefore, a smart framework is developed to categorise cardiac arrhythmias with the aim of resolving the issue. The aforementioned system makes use of the widely used random forest classifier[10]. In this study, RF is used to find the optimal combination of cardiac arrhythmia feature counts and predictive accuracy. The MIMIC-III dataset is used to assess the framework's efficiency. The grid search method and the genetic algorithm are contrasted based on their simulation findings. The suggested framework is claimed to be more accurate than competing methods. Early identification of lung cancer decreases the likelihood that the disease may spread to other parts of the body. Therefore, a computer-assisted framework is developed to detect lung cancer at an early stage, allowing for more accurate detection. Metastasis data and a deep learning model constitute the basis of the proposed approach. In order to learn about metastatic spread, the medical body area network is being studied. For the purpose of making predictions, however, a deep learning model is used. Simulation results are compared with the conventional CNN method, and the performance of the new framework is assessed using a lung cancer dataset. It has been claimed that the suggested framework is more accurate than CNN at identifying those who have lung cancer.

Every fifth person in the globe now has diabetes, making it an extremely widespread illness in today's society. Obesity and insufficient physical activity contribute significantly to the diminished insulin production that underlies diabetes. Zhu et al. provide an enhanced diabetes diagnostic model based on logistic regression, principal component analysis, and K-Means for efficient treatment of the disease[11]. Using principal component analysis, the aforementioned model maps diabetes data to a reduced dimensional space. The PIMA Indian Diabetes Dataset is used to evaluate the effectiveness of the suggested model. It is also observed that the accuracy rate of diabetes prediction is much enhanced when PCA is combined with LR and KM. In addition, a dataset comprised of electronic health records is explored for testing the effectiveness of the suggested approach. The prediction rate of this model is greater than that of other algorithms in the same class.

Predicting whether or not a patient will develop diabetes is a challenging endeavour. The question of whether or not a person has diabetes was also discussed by Maniruzzaman et al. [12]. Therefore, a prediction system based on machine learning is created to correctly identify patients who are suffering from diabetes. There are two main components to the proposed system: (i) the p-value, and (ii) the odd ration. In addition, a classifier based on logistic regression is suggested for assessing the risk variables linked with each patient. In addition, four widely used classifiers—NB, DT, Adaboost, and RF—are implemented for use in the prediction job. The K2, K5, and K10 partitioning protocols' behaviours are also highlighted in this paper. When comparing the accuracy of various classifiers to the simulation results, it becomes clear that the combination of RF and the K10 protocol provides the highest accuracy by far.

In [13], we see a health monitoring system that uses cloud computing, ML, and IoT to keep tabs on people's well-being. The suggested healthcare system takes into account past data in order to provide a correct diagnosis for patients. It is also observed that past data may be accessed by a machine learning algorithm and is kept in the cloud. In addition, the suggested healthcare system may make choices about which patterns to keep in the database. The effectiveness of the proposed healthcare system is evaluated here using accuracy as a performance metric. The simulation results of the aforementioned healthcare system are compared across a broad range of ML classifiers. Algorithms such as SVM, MLP, KNN, DT, NB, and RF are examples. In addition, a broad range of illness datasets are used for evaluating the effectiveness of the proposed healthcare system, including liver disorders, surgical data, breast cancer, heart diseases, spect_heart, diabetes, thyroid, and dermatological data. It has been observed that the RF-based prediction model has a higher disease-prediction rate archive.

In [14] proposed an enhanced model, named HealthFog, for automated and precise analysis of heart disease. Deep learning and edge computing are both components of the HealthFog system. The proposed HealthFog system relies on a fog layer to handle user requests on behalf of Internet of Things (IoT) devices and patient data. In this study, we introduce FogBus, a new performance metric that incorporates a number of other metrics such as power use, jitter, bandwidth, accuracy, execution time, and latency. The suggested HealthFog-based approach is shown to greatly enhance service quality and prediction accuracy.

In medical informatics, missing data imputation is a major challenge. Most studies throw out processed data because of missing data instances. However, this has the potential to introduce bias into important fields like medicine. Therefore, Daberdaku et al. [15] investigated the weighted KNN method and linear interpolation for missing value calculation in longitudinal clinical data. The distance between data points is calculated using weighted KNN, where the weight is determined by the maximum information coefficient. Several approaches for computing missing values are compared to the simulation results of the suggested method. It is claimed that the suggested combination outperforms the current one in terms of accuracy thanks to the efficient calculation of missing values in the dataset.

The prediction results may be skewed if there are missing values in the datasets used. A novel threshold-distance-based weighted imputation approach was developed by Cheng et al. [16]. Using the suggested technique, the k-number of missing value of incomplete data instances may be calculated, and the best possible value can be evaluated to fill the gaps. The suggested approach gives a higher imputation rate compared to previous examined strategies when missing values are included. An auto encoder neural network-based missing value imputation method was developed by Choudhury and Pal [8]. The auto neural network is first trained without any missing data, and then the missing data is predicted using the previously described model. The auto encoder based data imputation strategy is compared to eight current imputation methods. The findings demonstrated that the auto encoder data imputation method outperformed the competition.

4. DEEP LEARNING TECHNIQUE

It is a machine learning paradigm that makes use of complicated interactions and various representation layers to describe and solve issues. In recent years, the CNN method has been widely used by researchers in quest of optimum solutions to a variety of optimisation issues. Prediction of stroke disease is also implemented using a CNN model in this paper. The input data is processed by the convolutional layer of a CNN model, which is the first layer of the model. Dataset characteristics are used to represent the kernels[17]. The goal of this effort is to produce a feature map for use as input in a subsequent layer.

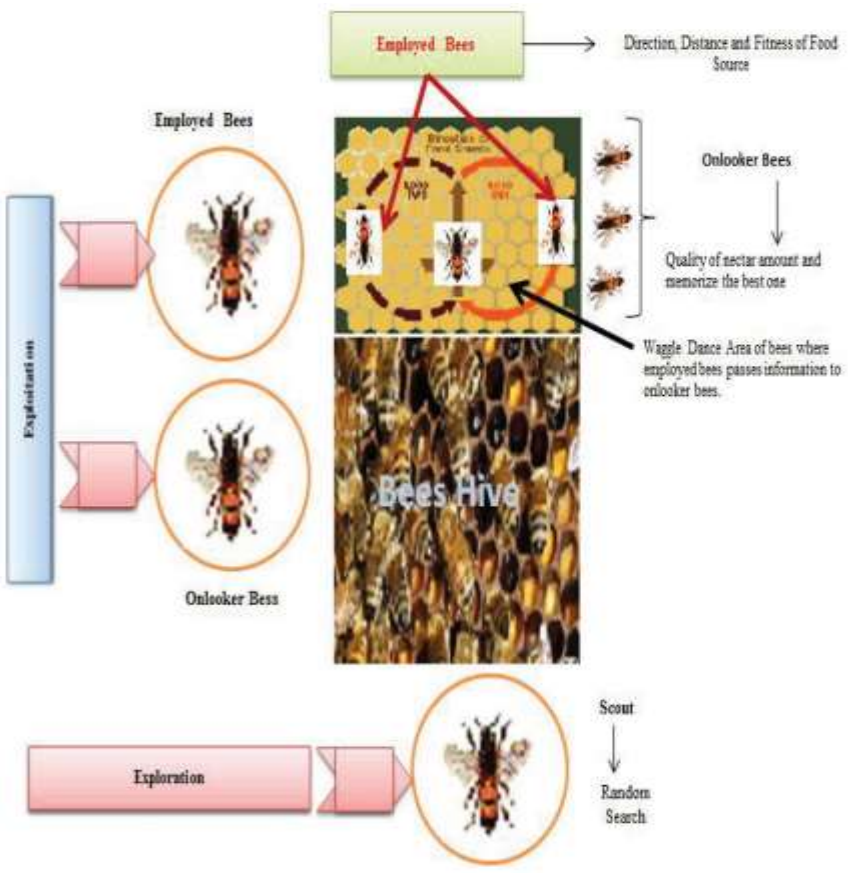

Figure.1: Forging behaviour of bees

The Max Pooling Layer takes the feature map as input, and its purpose is to ensure that only reliable data is passed on to the subsequent layers. In other words, this layer checks the feature-based accuracy of the convolutional layer's output via a chain of subsequent operations. The problem of data overfitting is likewise handled here at this layer. This layer also takes into account an activation function, whose job it is to fire the neurons, in order to achieve the best possible optimisations[18]. In addition, neurons may activate if the information they receive is suitable; if it isn't, the associated neuron will stay inactive. Each neuron is also assigned a numerical value using the activation function. As an activation function for the maximum pooling layer, the Tanh function is considered in this study. The effectiveness of the ABC-FS optimised DNN Model is measured using the three standard methods. The terms Accuracy and Effort explain these indicators of effectiveness. When applied to all data objects (true positive, false positive, true negative, and false instances), this metric identifies the properly categorised data items (true positive and true negative examples).

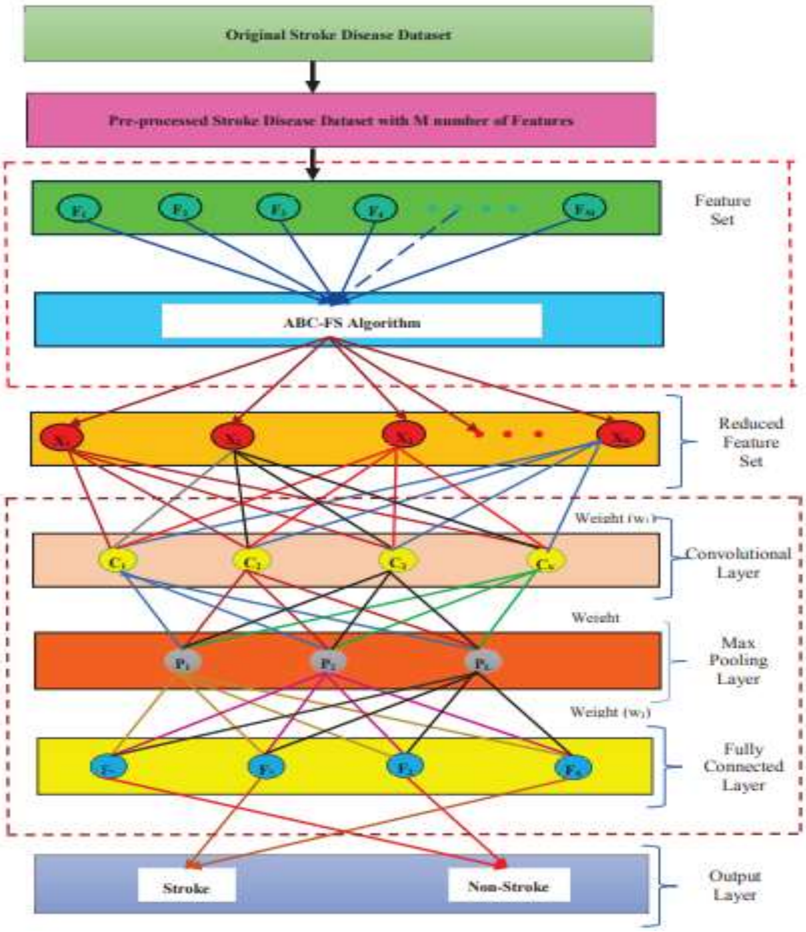

Figure .2: DNN-based diagnostic model schematic

According to the research, two of the most problematic aspects of medical data are missing values and identifying outliers. This study's goal is to solve the problems of missing values and unusual observations, two common types of medical data. Most research in the literature either disregard or remove the missing data from stroke dataset, indicating that these problems were not examined[19]. In order to accurately identify patients who have had a stroke, a hybrid stroke prediction framework has been suggested in this study. An outlier is a potentially serious problem in the field of medical informatics. Data's conduct differs from the rest of the dataset, according to one interpretation. A classifier's prediction rate may also be significantly impacted by an outlier. It is clear that the outlier can be dealt with efficiently using a clustering approach.

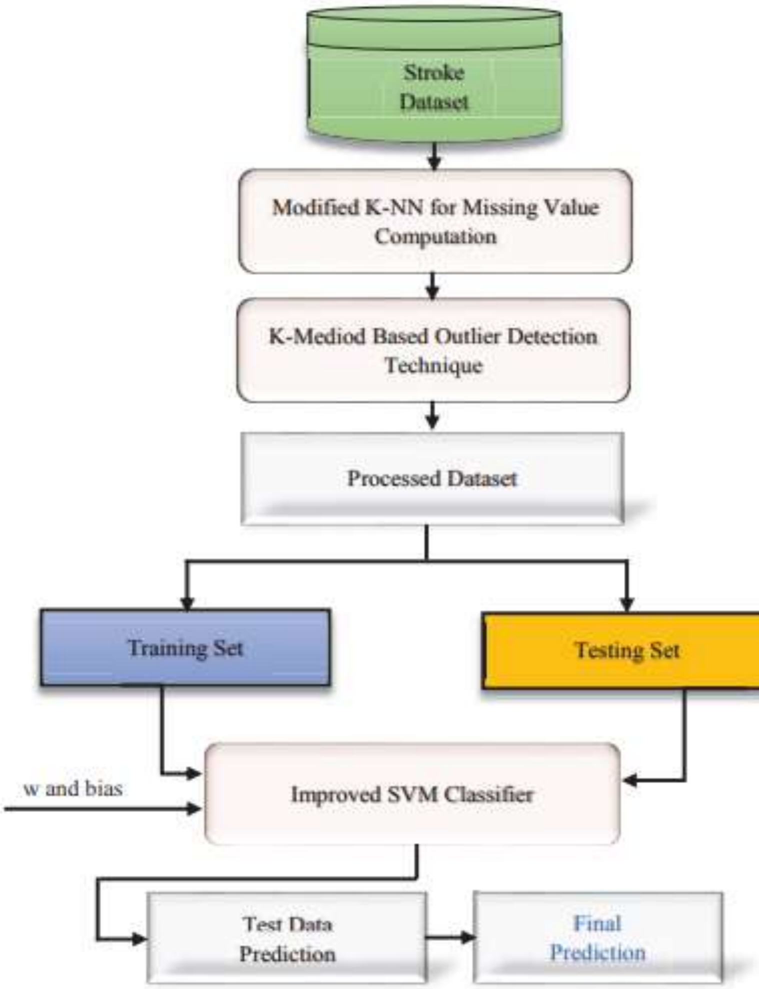

Figure.3: Model for predicting strokes, as suggested and illustrated

Methods, both statistical and heuristic, are given that can spot and deal with these anomalies. In this paper, we propose KM-PSO, an unsupervised approach based on the K-Mean and PSO for dealing with outliers in the stroke dataset[20]. While KM is used to identify the outlier in the stroke dataset, PSO is used to produce the first cluster centres for K-means. However, it has been shown that SVM may over fit the data several times, leading to subpar classifier performance. As a consequence, our study refines SVM to address the overfitting problem and enhance prediction accuracy. Least squares SVM is an example of a variant of SVM that seeks to address data overfitting by reducing the influence of SVM's underlying structural behaviour. In this study, we take into account this variant of SVM and enhance it by introducing new restrictions. Unbalanced restrictions may be made balanced in the latest iteration of SVM. The square of the error may be minimised in lieu of the negative error restriction to reach this goal. Therefore, linear programming, rather than quadratic, is used in the enhanced SVM. In addition, both margin and least square errors are minimised simultaneously, leading to more precise calculations.

5. RESULTS AND DISCUSSION

The experimental findings of the proposed stroke disease prediction framework utilising the stroke dataset are presented in this section. The suggested system combines a missing value calculation method based on k-NN, an outlier detection method based on KM-PSO, and an enhanced SVM classifier. The effectiveness of the stroke disease framework is assessed using a well-known dataset on the illness. The stroke dataset's seven hundred eighty-six data items have missing values. The stroke dataset's nine properties have empty fields. One thousand four hundred sixty seven missing values are present throughout the whole dataset. This approach uses k-NN to calculate the missing values. Additionally, it has been noted that the stroke dataset has a number of odd numbers that seem to be outliers. Therefore, a KM-PSO-based approach may be used to address the outlier issue in the stroke dataset. Finally, an enhanced SVM algorithm is used to accurately predict stroke disease. Accuracy, specificity, sensitivity, kappa, and AUC are just a few of the metrics taken into account while evaluating the effectiveness of the stroke prediction framework. The confusion matrix is made to assess the variables described above. Two hundred forty-nine data items are present in the no class, but four thousand eight hundred sixty-one data objects are present in the yes class. Four thousand five hundred fifty one data items are given real class labels using the k-NN approach; out of these, four thousand three hundred sixty three data objects are given the class yes, and one hundred eighty eight are given the class no. The stroke dataset also includes instances of inaccurate data that are deleted, and the remaining dataset's missing values are estimated using the closest neighbour technique. Four thousand five hundred fifty one data items total after missing value calculation in the stroke data set.

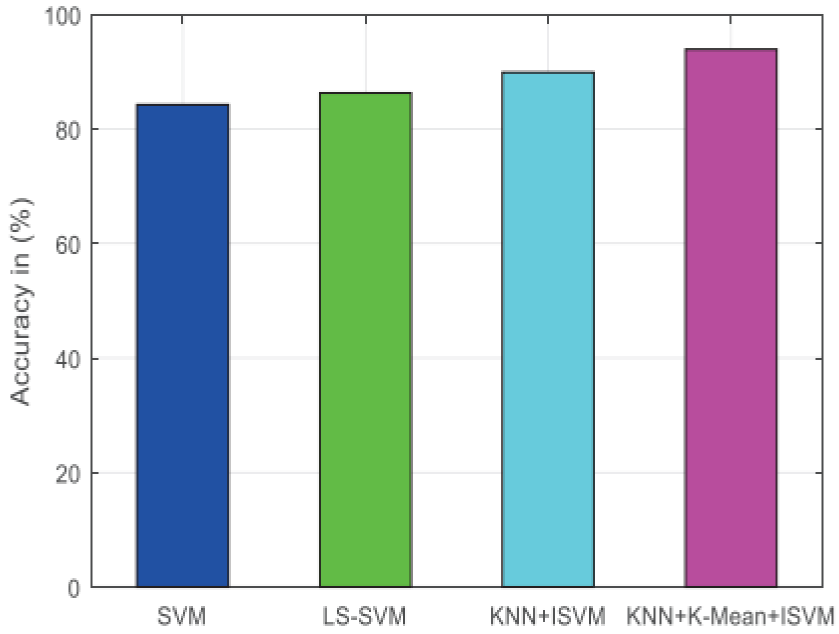

Figure .4: Accuracy rates of SVM, LS-SVM, K-NN+LS-SVM, and the proposed framework are compared.

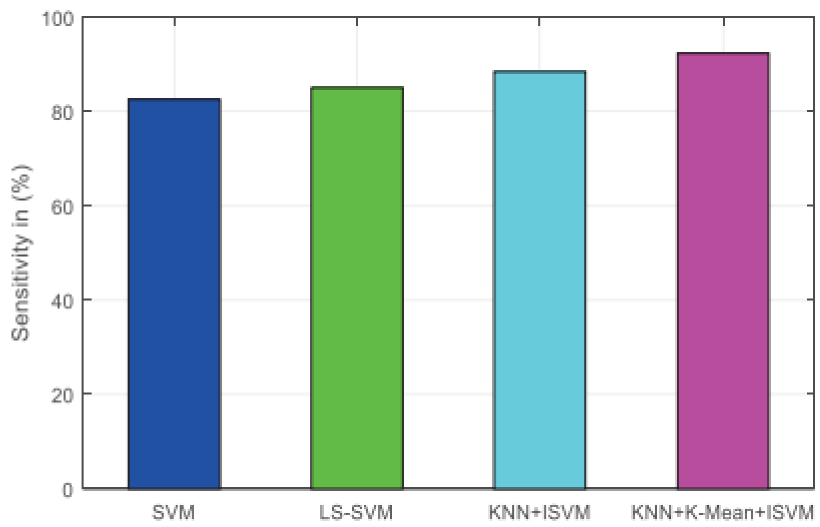

Figure.5: Sensitivity rates of SVM, LS-SVM, K-NN+LS-SVM, and the proposed framework are compared.

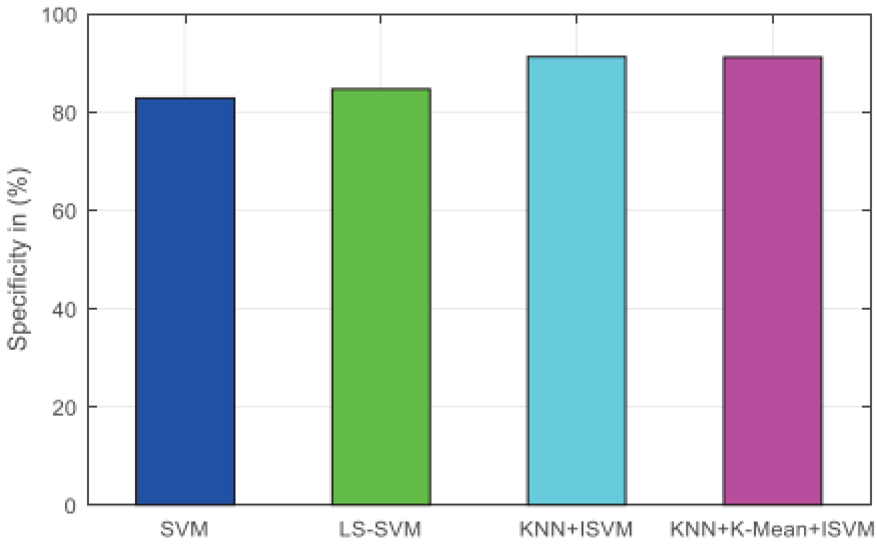

Figure.6: Specificity rates of SVM, LS-SVM, K-NN+LS-SVM, and the proposed framework are compared.

Figures 4 and 5 use accuracy and sensitivity indicators to show the experimental findings of SVM, LS-SVM, K-NN+ISVM, and KNN+KMPSO+ISVM. It is discovered that using the combination of K-NN+KMPSO+ISVM produces better outcomes than other methods. SVM's performance in diagnosing stroke illness is subpar since it cannot take into account missing values and outlier data. As a result, it can be claimed that outlier and missing value calculation have a big influence on prediction accuracy. The kappa, AUC, and specificity rates are used to assess the outcomes. These signs are important and have a greater influence on the medical diagnosis procedure. The results of all SVM variants' specificity tests are shown. It was shown that KNN+KMPSO+ISVM outperforms other approaches in terms of specificity. The relationship between sensitivity and specificity is shown by this indicator. In the instance of the kappa indicator, the number larger than 8 should be more relevant. The KNN+KMPSO+ISVM strategy, however, obtains more than 9 kappa values despite the fact that all strategies reach more than 8 kappa values. The association between the TP rate and FP rate is also shown by the AUC indicator.

6. CONCLUSION

The capacity of machine learning algorithms and the Internet of Things to provide reliable and feasible solutions for illness detection and prediction is explored in this study. To identify the gaps in the body of work already done, a variety of applications of machine learning algorithms and IoT are explored. Accurate forecasting is cited as one of the major problems with medical data. In certain healthcare datasets, the bulk of data instances belong to the negative class, while only a small number are associated with the positive class. This results in a class imbalance issue. Additionally, it is observed that certain values in the provided dataset are missing, and whenever a classifier is used for a prediction job, the accuracy is constantly in doubt. Dealing with the missing data values is thus an essential step for improving accuracy. On the other hand, IoT has a great deal of flexibility in the healthcare sector and also offers potential solutions for it. Three methods are developed in this work for the effective management, monitoring, and prediction of illness datasets. The stroke dataset is also taken into account in this study while using the aforementioned strategies.

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