2022 5th Information Technology for Education and Development (ITED)

A Machine Learning Technique for Detection of Diabetes Mellitus

Awoniran, O. M.
Computer Science Program,
Bowen University,
Iwo, Nigeria.
lekanawoniran@gmail.com

Oyelami, M. O.
Computer Science Program,
Bowen University,
Iwo, Nigeria.
olufemi.oyelami@bowen.edu.ng

Ikono, R. N.
Department of Computer Science and Engineering,
Obafemi Awolowo University,
Ile-Ife, Nigeria.
rudo@oauife.edu.ng

Famutimi, R. F.
Computer Science Program,
Bowen University,
Iwo, Nigeria.
ranti.famutimi@gmail.com

Famutimi, T. I.
Computer Science Program,
Bowen University,
Iwo, Nigeria.
ifeoluwatemitayo@gmail.com

Abstract **— The need for early detection of diabetes mellitus has led to the development of various intelligent systems using machine learning and artificial intelligence for the recognition of the presence of the disease. However, most of the techniques have yielded a comparatively lower accuracy. This research applied data science techniques to a dataset of diabetes mellitus to improve the accuracy of the prediction of the disease. This was achieved by pre-processing the data with dummy categories and applying principal components analysis for reduced dimensionality. Support vector machine, random forest classifier, and deep neural networks were then used to train the system. Support vector machine, random forest classifier, and deep neural networks yielded accuracies of 0.76, 0.77, and 0.89 respectively. Correspondingly, deep neural networks yielded the highest accuracy. The study concluded that better pre-processing will improve the accuracy of machine learning algorithms in the prediction of diabetes mellitus.**

Keywords — Data Science, Machine Learning, Artificial Intelligence, Diabetes

I. Introduction

Diabetes is a metabolic disease that increases the blood count of sugar in the blood [1]. This is caused either by the inability of the body to produce enough insulin that converts excess blood in the sugar to glycogen or when the body becomes resistant to insulin that it produces by itself thereby causing it not to be able to convert the excess sugar in the body to glycogen [2-4]. In both cases, there is excess sugar in the blood, thereby resulting in the disease known as diabetes. The first scenario is known medically as "Type-1 Diabetes" while the second is regarded as "Type-2 Diabetes". The third type of diabetes is known as gestational diabetes and it is witnessed by some pregnant women due to hormonal imbalances in the body during pregnancy [5].

Although the physiological effects of the various forms of the disease are quite similar, it is worth of note that Type-2 diabetes is the most common type. Common symptoms of the disease include frequent urination, burning thirst, feeling famished, extreme fatigue, blurry vision, slow healing cuts/bruises, weight loss (type 1), tingling, pain, or numbness in the hands/feet (type 2) [6].

Clinically, the detection of the disease is done by carrying out various medical and laboratory tests. Risk factors associated with the disease include high blood glucose, a history of gestational diabetes, high blood pressure, skin thickness, low insulin levels, disproportionate body mass index (BMI), and a family history of the disease [7].

Furthermore, each of the specific risk factors that are associated with the disease has an associated threshold that is suggestive of the likely presence of the disease in an individual. However, the attainment of this value for any isolated risk factor may not necessarily be indicative of the presence of the disease. Therefore, having an effective predictive system based on the risk factors associated with the disease becomes of high importance in the effective diagnosis of the disease. This will also facilitate the early detection and management of the disease [8].

Early disease detection is important in the treatment and management of the various types of Diabetes Mellitus [9]. Most of the current methods for the identification of the disease are clinically based. Correspondingly, people are required to visit clinics and other medical facilities to get tested before they can be diagnosed with the disease. However, there is a substantial risk of people presenting the disease at an advanced stage with this current technique [10].

Recent advances in data science, machine learning, and artificial intelligence (AI) have resulted in the provision of intelligent systems, decision support systems, and the enablement of ambient intelligence [11]. This is evident in various research areas such as natural language processing, image processing, fraud detection, disease diagnosis, etc. The ability to forecast and predict gives AI systems priority over conventional systems [12]. The predictive capability of AI systems falls under the supervised learning category. This involves classifying a set of independent variables into a category of outcomes, the dependent variables. Various machine and deep learning techniques have been proposed for this [13].

This research aims to develop an intelligent system for the prediction of diabetes mellitus and compare the performances of various machine learning algorithms in the prediction of the disease. This paper is structured as follows: Section I gives an introduction and background to the research; Section II reviews existing works that are related to intelligent systems in diseases prediction; Section III discusses the methods employed in carrying out the research work; Section IV presents the results obtained and their discussions; Finally, Section V concludes the research work.

978-1-6654-9370-3/22/$31.00 ©2022 IEEE

II. LITERATURE REVIEW

An attempt to predict diabetes using various machine-learning techniques were carried out by Mujumdar and Vaidehi [14]. The work adopted the use of external factors along with those responsible for diabetes. The classification was then boosted with additional datasets and a pipeline model for prediction was adopted. The work recorded higher performances with the additional datasets in the building of the machine learning pipeline. It is, however, unclear how the additional dataset influenced the estimation of better results.

Mitushi and Varma [15] also made attempts to predict the disease. The research aimed to predict diabetes by analyzing different human body attributes. The methodology adopted in the work involves using support vector machines (SVM), K-nearest neighbours (KNN), random forests (RF), decision trees (DT), logistic regression (LogReg), and Gradient Boosting (GB) classifiers for the prediction. The research obtained a maximum accuracy of 77% [14]. Implicatively, the prediction will only be correct seventy-seven times out of a hundred times.

Neha and Shruti [16] also attempted to predict Type-II diabetes using machine learning techniques. The research aimed to assess the risk of diabetes among individuals based on their lifestyles and family backgrounds. The research adopted LogReg, KNN, SVM, Naïve-Bayes (NB), DT, and RF in the prediction of type-II diabetes intending to reduce the prevalence of the ailment. RF yielded an accuracy of about 94% for the experiment conducted on a dataset of health, lifestyles, and family backgrounds as obtained by the researchers. However, an accuracy of 75% was obtained when the same algorithm was used on a dataset of diabetes risk factors.

Several attempts have been made to predict diabetes using machining learning and most of the attempts largely relied on machine learning algorithms. Most of these attempts have been carried out to seek the best algorithm that could be useful in the prediction of the disease. However, research on how best the data can be pre-processed for better machine learning has not been explored The accuracy of the current methods can be improved if techniques that better expose the independent variables to better machine learning algorithms are adopted.

III. METHODOLOGY

The methodological framework adopted in the research work has 6 phases. The first phase of the research is problem analysis. Thereafter, data gathering, exploratory data analysis, system training, analysis of the obtained results, and system implementation phases were carried out. Fig. 1 outlines the various phases of the methodological framework and the following subsection discusses the various phases.

A. Data Gathering

The diabetes dataset was obtained from the National Institute of Diabetes and Digestive and Kidney Diseases through the Kaggle data-sharing application (https://www.kaggle.com/datasets/mathchi/diabetes-data-set). The obtained contains 768 instances with eight independent variables and one dependent variable. Table 1 describes the various variables.

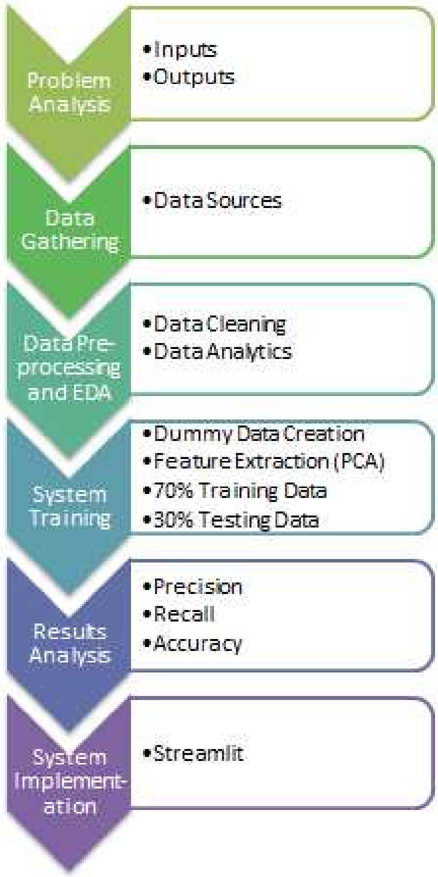

Fig. 1: The Methodological Framework

TABLE I. THE VARIABLES IN THE DATASET

S/N	Variable	Description
1	Pregnancies	Number of times pregnant
2	Glucose	Plasma glucose concentration a 2 hours in an oral glucose tolerance test
3	Blood Pressure	Diastolic blood pressure (mm Hg)
4	Skin Thickness	Triceps skin fold thickness (mm)
5	Insulin	2-Hour serum insulin (mu U/ml)
6	BMI	Body mass index (weight in kg/(height in m)^2)
7	Diabetes pedigree function	A measure of susceptibility to diabetes due to family background
8	Age	Age in years
9	Outcome	Class variable (0 for negative or 1 positive)

B. Data Cleaning, Data Pre-processing and Exploratory Data Analysis

Data cleaning was carried out to get rid of incorrect and incomplete data. In doing this, missing, null, and invalid data were sought in the dataset and removed. Afterward, data pre-processing was carried out [17].

Again, to better expose the data for machine learning, data pre-processing was carried out. To carry this out, the ages of individual data records were classified into 3 groups. The first group is those less than 40 years, the second group is those between 41 and 59 years, and the last group is those that are above 60 years. Finally, dummy variables were created for the three groups. However, the first group was dropped before the application of machine learning algorithms to the dataset to avoid the dummy variable trap [18]. Afterward, exploratory data analysis was then carried out to understand the relationships between the various independent data. In doing this, count plots, joint plots, and kernel density estimation plots were carried out.

C. System Training

In training the system, feature extraction was initially carried out to reduce the number of features that the data will be trained on. Thereafter, Support Vector Machine (SVM), Random Forests Classifiers (RFC), and Deep Neural Networks algorithms were used to train the system.

1) Feature Extraction using Principal Components Analysis: Principal components analysis (PCA.) is a dimensionality reduction technique for reducing the dimensionality of datasets [19]. The technique reduces the number of independent variables of a dataset while maintaining their information to a large extent. PCA geometrically reduces data dimensionality by projecting them on lower dimensions known as principal components to compute a summary of the data using limited principal components [20]. PCA was applied to the gathered dataset and the dimensionality of the dataset was reduced from ten to two [21-22].

2) System Training using Support Vector Machine: Support vector machine (SVM) is a machine learning algorithm that is used for solving classification and regression-based problems [23]. In SVM, each data point is plotted in an n-dimensional graph with each data feature representing a dimension in the space. Classifications are then carried out by locating hyper-planes that most differentiate the classes in the dataset [24].
SVM was applied to the gathered data to train the AI system and make predictions. The performance of the algorithm in making predictions on diabetes was then taken.

3) System Training using Random Forest Classifier: A random forest classifier (RFC) is an ensemble learning method and meta-estimator that classifies data by fitting decision tree classifiers, which are constructed at the time of training, on data points of the dataset [25]. The algorithm also uses an averaging technique to improve the predictive accuracy of the algorithm and as well as control over-fitting. The output of the algorithm is the category class selected by most trees in the algorithm [26]. RFC was applied to the gathered data to train the AI system and make predictions. The performance of the algorithm in making predictions on diabetes was then taken.

4) System Training using Deep Neural Network: Deep neural network (DNN) is a stacked neural network that comprises several layers of interconnected artificial neural layers [27-28]. DNNs can model complex non-linear relationships. DNN, like other neural network architecture, takes inputs, makes mathematical computations, and produces an output if a threshold value for an artificial neuron is reached [29-30]. The activation of the neurons at various layers depends on the threshold value as well as the adopted activation function. The ReLU and Softmax activation functions were adopted in the design of the DNN model [31]. DNN was applied to the gathered data to train the AI system and make predictions. The performance of the algorithm in making predictions on diabetes was then taken.

IV. Results

A count plot of the possible outcomes is shown in Fig. 2. The blue represents the outcome "0" which is the people without the disease, while the red represents the outcome "1" which is people with the disease. From the Figure, it can be seen that there are about 500 individuals without the disease while about 268 individuals have the disease.

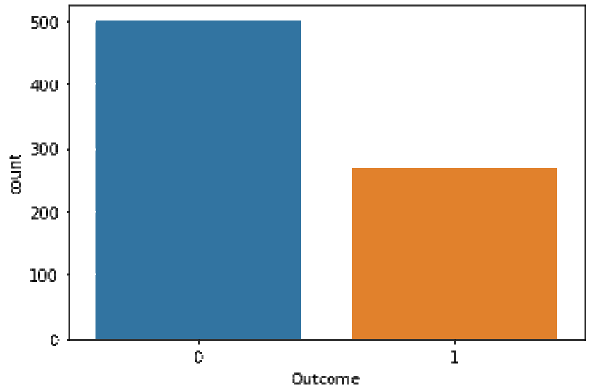

Fig. 2: A Count Plot of the Possible Outcomes

As discussed in the methodology, the individuals were separated into 3 different age groups. The first group is those who are 40 years old or less (group 0), the second group is those between 41 and 59 years old inclusively (group 1), and the last group is those that are 60 years old or older (group 2). Fig. 3 shows that a greater percentage of people with the disease are those less than 40 years old.

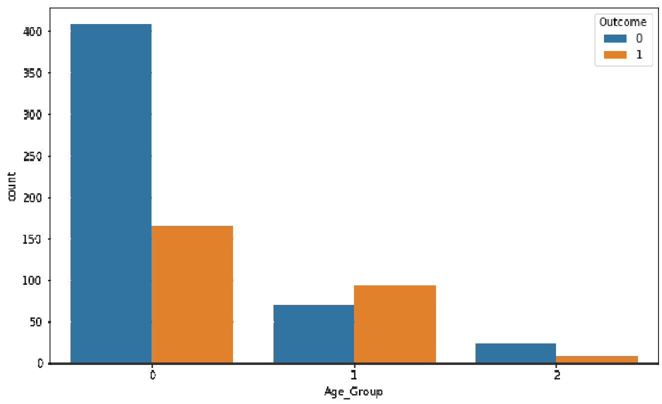

Fig. 3: A Count Plot of the Age Groups of the Individuals

Also, the same was done for the glucose level in the blood of the individuals and this is shown in Fig. 4. Group 0 is those with glucose levels of less than 90, group 1 is those with glucose levels that are between 90 and 125 inclusively, while the last group is those with glucose levels that is more than 125. It can be seen that those with glucose levels of more than 125 are more likely to have the disease.

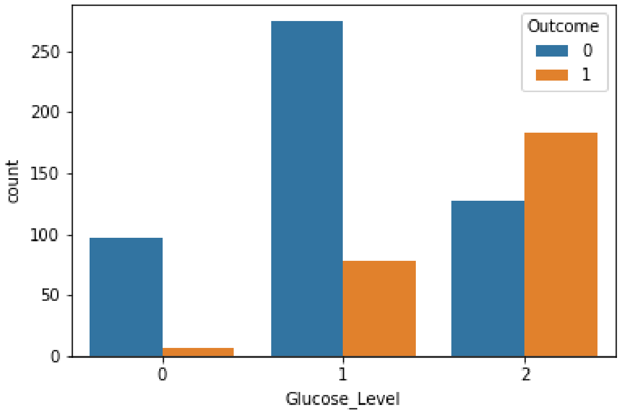

Fig. 4: A Count Plot of the Glucose Levels of the Individuals

Fig. 5 shows a plot of the "Pregnancies" against age. The figure shows that those that are within the childbearing age are more in the dataset. This is to cater to gestational diabetes. Fig. 6 shows that those with the disease (red) have a higher kernel density than those without it (blue).

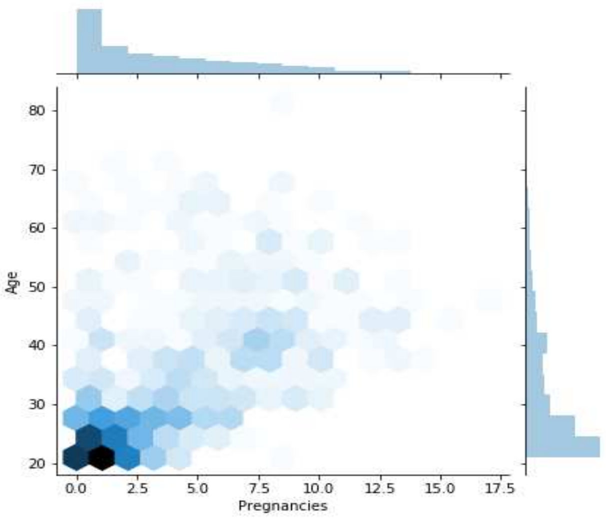

Fig. 5: A Joint Plot of the Pregnancies against the Ages

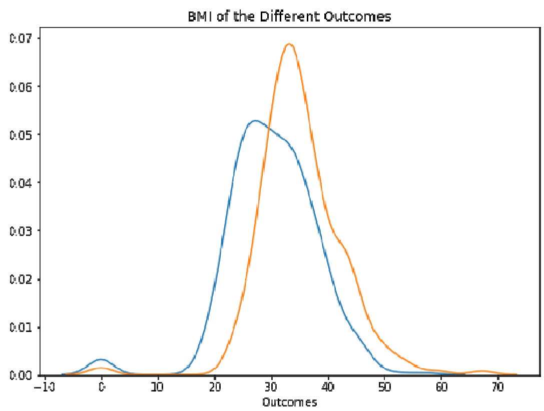

Fig. 6: A KDE Plot of the Glucose Levels of the Individuals

As part of the data cleaning process, the data was examined for null values. Null values are empty cells or incomplete records that might be in the dataset. In very large data sets, such records might be dropped, but since the dataset is within the medium range, replacing empty cells with the average of the columns would be done. However, there were no empty cells in the dataset.

Furthermore, a dummy variable was created for the created "Age Groups" column. This was done by creating 3 columns in the data set and assigning a "1" to the column which corresponds to the age group to which a specific record belongs. Correspondingly, a "0" is assigned to the two other columns to which the specific record does not belong.

Finally, the first column out of the 3 was dropped. This is done to have uniqueness among the 3 possible age groups and to avoid the dummy variable trap. Also, the initial "Age" column and the created "Age Group" column were dropped to avoid diffusion and over-fitting. The head row (2 rows) of the final dataset for the supervised learning for diabetes prediction is given in Table II.

TABLE II. THE HEAD SECTION (FIRST 2 RECORDS) OF THE PREPARED DATASET

	Preg	Gl.	BP	Skin Thick.	Ins.	BMI	DBF	1	2
0	6	148	72	35	0	33.6	0.627	1	0
1	1	85	66	29	0	26.6	0.351	0	0

As discussed in the methodology, SVM, RFC, and DNN (using TensorFlow) were used for the machine learning. In all cases, the data were randomly divided into 2; 70% for training and 30% for testing. Also, as earlier stated, outcome "0" are individuals without the disease while outcome "1" are individuals suffering from the disease.

The results obtained from the various algorithms are discussed as follows:

A. Support Vector Machine (SVM)

Support vector machine classifies data by attempting to estimate support vectors (borders) in the data set. SVM recorded a negative predictive value (NPV) of 0.76 and a positive predictive value (PPV) of 0.77. It recorded a true negative rate (TNR) of 0.93 and a true positive rate (TPR) of 0.46. The harmonic mean of precision and recall (F1-score) recorded are 0.83 and 0.57 for the “0” and “1” outcomes respectively. The measure of correct prediction (accuracy) of the algorithm is 0.76.

B. Random Forest Classifier (RFC)

Random forest classifier fits decision trees on a sample set of data from the dataset. The method improves accuracy by averaging. 200 estimators were used in building the classifier. RFC recorded a negative predictive value (NPV) of 0.81 and a positive predictive value (PPV) of 0.68. It recorded a true negative rate (TNR) of 0.84 and a true positive rate (TPR) of 0.64. The harmonic mean of precision and recall (F1-score) recorded are 0.83 and 0.66 for the “0” and “1” outcomes respectively. The measure of correct prediction (accuracy) of the algorithm is 0.77.

C. Deep Neural Network (DNN)

A deep neural network creates multi-directional dense layers of artificial neural network (ANN) between input and output layers. Before using the DNN, the values of the dataset were initially scaled to normalize the data. 3 layers of DNN were then applied in training the data set. DNN recorded a negative predictive value (NPV) of 0.83 and a positive predictive value (PPV) of 0.71. It recorded a true negative rate (TNR) of 0.85 and a true positive rate (TPR) of 0.68. The harmonic mean of precision and recall (F1-score) recorded are 0.84 and 0.69 for the "0" and "1" outcomes respectively. The measure of correct prediction (accuracy) of the algorithm is 0.89.

V. Discussion

The model development and evaluation phase resulted in SVM recording an accuracy of 76%, RFC recording an accuracy of 77%, and DNN recording an accuracy of 89%. A comparative performance table for the 3 algorithms used for the prediction of the disease is shown in Table III.

TABLE III. Comparative Performance Table of the Algorithms used in the Prediction of Diabetes

Algorithm / Metric	SVM	RFC	DNN
NPV	0.76	0.81	0.98
PPV	0.77	0.68	0.87
TNR (Specificity)	0.93	0.84	0.92
TPR (Sensitivity)	0.46	0.64	0.79
F-Measure (Negative)	0.83	0.83	0.95
F-Measure (Positive)	0.57	0.66	0.83
Accuracy	**0.76**	**0.77**	**0.89**

From Table III, it can be deduced that given the dataset, SVM will be able to predict the presence of the disease at a rate of 76%, RFC at a rate of 77%, and DNN at a rate of 89%. It can be seen that there is comparative improvement in the accuracy of the result obtained from previous research carried out in the application of machine learning to the prediction of diabetes mellitus.

This is because of the pre-processing methods adopted in the research work. The methods allowed for better adjustments from the machine learning algorithms. The better adjustments then form the basis for the improved results recorded by the algorithms.

VI. Conclusion

The adoption of methods that better expose the dataset to the machine learning algorithms improved the performance and accuracy of the various machine learning algorithms adopted in the research. This is because doing so creates a clear separation between the various data points that are significant in the classification of the outcomes of the algorithm and implicatively, the disease.

Again, the comparative analysis of the results obtained from the various algorithms indicates that deep neural networks recorded the highest accuracy in the prediction of the disease. Therefore, DNN should be adopted in the implementation of an intelligent system for the prediction of the disease.

Conclusively, the application of machine learning techniques and most importantly, the deep neural networks technique on adequately processed data proved effective in the prediction of diabetes mellitus.

References

[1] Al-Ishaq, R. K., Abotaleb, M., Kubatka, P., Kajo, K., & Büsselberg, D. (2019). Flavonoids and their anti-diabetic effects: cellular mechanisms and effects to improve blood sugar levels. Biomolecules, 9(9), 430.

[2] Balaji, R., Duraisamy, R., & Kumar, M. P. (2019). Complications of diabetes mellitus: A review. Drug Invention Today, 12(1).

[3] Mukhtar, Y., Galalain, A., & Yunusa, U. (2020). A modern overview on diabetes mellitus: a chronic endocrine disorder. European Journal of Biology, 5(2), 1-14.

[4] Gambo, I., Massenon, R., Yange, T.S., Ikono, R., Omodunbi, T., Babatope, K. (2021). Software Design Specification and Analysis of Insulin Dose to Adaptive Carbohydrate Algorithm for Type 1 Diabetic Patients. In: Patgiri, R., Biswas, A., Roy, P. (eds) Health Informatics: A Computational Perspective in Healthcare. Studies in Computational Intelligence, vol 932. Springer, Singapore. https://doi.org/10.1007/978-981-15-9735-0_7

[5] Gollapalli, M., Alansari, A., Alkhorasani, H., Alsubaii, M., Sakloua, R., Alzahrani, R., & Albaker, W. (2022). A novel stacking ensemble for detecting three types of diabetes mellitus using a Saudi Arabian dataset: pre-diabetes, T1DM, and T2DM. Computers in Biology and Medicine, 147, 105757.

[6] Huifen, H., Xuelin, Z., Liang, F., & Haiyan, D. (2020). Effect of Jiangtangning Capsule Combined with Acarbose on Blood Glucose and Islet β Cell Function in Patients with Type 2 Diabetes. Modern Journal of Integrated Traditional Chinese and Western Medicine, 15(15), 1669.

[7] Shafaeizadeh, S., Harvey, L., Abrahamse-Berkeveld, M., Muhardi, L., & M. van der Beek, E. (2020). Gestational diabetes mellitus is associated with age-specific alterations in markers of adiposity in offspring: a narrative review. International journal of environmental research and public health, 17(9), 3187.

[8] Petersmann, A., Müller-Wieland, D., Müller, U. A., Landgraf, R., Nauck, M., Freckmann, G., & Schleicher, E. (2019). Definition, classification and diagnosis of diabetes mellitus. Experimental and Clinical Endocrinology & Diabetes, 127(S 01), S1-S7.

[9] Herman, W. H., Ye, W., Griffin, S. J., Simmons, R. K., Davies, M. J., Khunti, K., Rutten, G. E., Sandbaek, A., Lauritzen, T., Borch-Johnsen, K., Brown, M. B., & Wareham, N. J. (2015). Early Detection and Treatment of Type 2 Diabetes Reduce Cardiovascular Morbidity

and Mortality: A Simulation of the Results of the Anglo-Danish-Dutch Study of Intensive Treatment in People With Screen-Detected Diabetes in Primary Care (ADDITION-Europe). Diabetes care, 38(8), 1449–1455. https://doi.org/10.2337/dc14-2459

[10] Harman, N. L., Wilding, J., Curry, D., Harris, J., Logue, J., Pemberton, R. J., & Williamson, P. R. (2018). Selecting Core Outcomes for Randomised Effectiveness trials In Type 2 Diabetes (SCORE-IT): study protocol for the development of a core outcome set. Trials, 19(1), 1-6.

[11] Kibria, M. G., Nguyen, K., Villardi, G. P., Zhao, O., Ishizu, K., & Kojima, F. (2018). Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks. IEEE access, 6, 32328-32338.

[12] Ngarambe, J., Yun, G. Y., & Santamouris, M. (2020). The use of artificial intelligence (AI) methods in the prediction of thermal comfort in buildings: Energy implications of AI-based thermal comfort controls. Energy and Buildings, 211, 109807.

[13] Ngiam, K. Y., & Khor, W. (2019). Big data and machine learning algorithms for health-care delivery. The Lancet Oncology, 20(5), e262-e273.

[14] Mujumdar, A. and Vaidehi V. (2019). Diabetes Prediction using Machine Learning Algorithms, Procedia Computer Science, Volume 165, Pages 292-299, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2020.01.047.

[15] Mitushi S. and Varma, S. (2020). Diabetes Prediction using Machine Learning Techniques, International Journal of Engineering Research & Technology (IJERT) 09(09). IJERTV9IS090496.

[16] Tigga N. P. and Garg, S. (2020) Prediction of Type 2 Diabetes using Machine Learning Classification Methods, Procedia Computer Science, Volume 167, Pages 706-716, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2020.03.336.

[17] Kumar, V., Roche, C., Overman, S., Simovitch, R., Flurin, P. H., Wright, T., Zuckerman, J., Routman, H., & Teredesai, A. (2020). What Is the Accuracy of Three Different Machine Learning Techniques to Predict Clinical Outcomes After Shoulder Arthroplasty?. Clinical orthopaedics and related research, 478(10), 2351–2363. https://doi.org/10.1097/CORR.0000000000001263

[18] Jung, S. H., Chen, Y., & Ahn, H. (2014). Type I error control for tree classification. Cancer informatics, 13(Suppl 7), 11–18. https://doi.org/10.4137/CIN.S16342

[19] Salem, N., & Hussein, S. (2019). Data dimensional reduction and principal components analysis. Procedia Computer Science, 163, 292-299.

[20] Lever, J., Krzywinski, M., & Altman, N. (2017). Points of significance: Principal component analysis. Nature methods, 14(7), 641-643.

[21] Tadist, K., Najah, S., Nikolov, N.S., Mrabti, F., and Zahi, A. (2019). Feature selection methods and genomic big data: a systematic review. J Big Data 6, 79 (2019). https://doi.org/10.1186/s40537-019-0241-0

[22] Divya, J. and Vijendra, S. (2018). Feature selection and classification systems for chronic disease prediction: A review. Egyptian Informatics Journal, 19(3), 179-189, ISSN 1110-8665, https://doi.org/10.1016/j.eij.2018.03.002.

[23] Cervantes, J., Garcia-Lamont, F., Rodríguez-Mazahua, L., & Lopez, A. (2020). A comprehensive survey on support vector machine classification: Applications, challenges and trends. Neurocomputing, 408, 189-215.

[24] Blonder, B., Morrow, C. B., Maitner, B., Harris, D. J., Lamanna, C., Violle, C.,. & Kerkhoff, A. J. (2018). New approaches for delineating n - dimensional hypervolumes. Methods in Ecology and Evolution, 9(2), 305-319.

[25] Ahmad, G. N., Fatima, H., Abbas, M., Rahman, O., & Alqahtani, M. S. (2022). Mixed Machine Learning Approach for Efficient Prediction of Human Heart Disease by Identifying the Numerical and Categorical Features. Applied Sciences, 12(15), 7449.

[26] More, A. S., & Rana, D. P. (2017, October). Review of random forest classification techniques to resolve data imbalance. In 2017 1st International Conference on Intelligent Systems and Information Management (ICISIM), 72-78. IEEE.

[27] Fang, S. H., Fei, Y. X., Xu, Z., & Tsao, Y. (2017). Learning transportation modes from smartphone sensors based on deep neural network. IEEE Sensors Journal, 17(18), 6111-6118.

[28] D'Angelo, G., & Palmieri, F. (2021). A stacked autoencoder - based convolutional and recurrent deep neural network for detecting cyberattacks in interconnected power control systems. International Journal of Intelligent Systems, 36(12), 7080-7102.

[29] Tian, Y., Pei, K., Jana, S., & Ray, B. (2018). Deeptest: Automated testing of deep-neural-network-driven autonomous cars. In Proceedings of the 40th international conference on software engineering (pp. 303-314).

[30] George, A. M., Banerjee, D., Dey, S., Mukherjee, A., & Balamurali, P. (2020). A reservoir-based convolutional spiking neural network for gesture recognition from dvs input. In 2020 International Joint Conference on Neural Networks (IJCNN) (pp. 1-9). IEEE.

[31] Zhang, X., Zou, Y., & Shi, W. (2017). Dilated convolution neural network with LeakyReLU for environmental sound classification. In 2017 22nd international conference on digital signal processing (DSP) (pp. 1-5). IEEE