Cognitive Model to Forecast Treatment Plans for T2D Patients with Various Risk Evaluations

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Abstract- The long-term management of chronic conditions such as Type 2 Diabetes (T2D) necessitates individualized patient care, given the variability in patient characteristics. The wealth of electronic records containing data on T2D patients presents opportunities for leveraging big data analysis to gain deeper insights into the manifestation of the disease and its impact on patients. Data science within the realm of healthcare holds the potential to unearth concealed knowledge from these databases, reaffirm existing insights, and facilitate the customization of treatment. In this research, we introduce a comprehensive set of data analytics tools for managing T2D, enabling healthcare professionals and researchers to uncover correlations between various biological markers in patients and the complications associated with T2D. This suite of analytics encompasses exploratory, predictive, and visual analytics, featuring functionalities such as the multi-tier classification of T2D patient profiles, linking them to specific conditions, forecasting the risk of T2D-related complications. The analytics methodologies presented in this project explore advanced data analysis techniques that have the potential to serve as valuable decision-making aids for clinicians, ultimately contributing to more effective T2D management.

Keywords- Type2 Diabetes, Support Vector Machine (SVM), Confusion Matrix, Health Records, Risk Forecasting, Treatment Response Prediction, Predictive Analytics, Chronic Disease Prediction.

I. INTRODUCTION

Type 2 Diabetes is a growing global health concern, posing a significant challenge to healthcare systems worldwide. The disease's prevalence is driven by factors such as sedentary lifestyles, unhealthy dietary habits, and an aging population. The burden of Type 2 Diabetes extends beyond its direct impact on individuals, encompassing economic ramifications and straining healthcare infrastructures. The multifaceted nature of the condition, characterized by insulin resistance and impaired glucose regulation, necessitates comprehensive strategies in prevention and management. As societies grapple with the rising prevalence of this condition, there is an urgent need for innovative approaches, including predictive modelling, to identify at-risk individuals early on, enabling timely interventions and reducing the overall burden on healthcare systems. The development of accurate and reliable predictive models, such as those employing Support Vector Machines (SVM), holds promise for enhancing our capacity to tackle this global health challenge effectively. Early detection in managing

Type 2 Diabetes plays a pivotal role in improving health outcomes, reducing complications, and alleviating the burden on healthcare resources. Predictive models empower healthcare professionals to identify individuals at risk of developing Type 2 Diabetes even before overt clinical symptoms manifest, allowing for personalized preventive strategies and lifestyle modifications that significantly reduce the likelihood of diabetes onset.

3. Objective

The development of a predictive model for Type 2 Diabetes using Support Vector Machines (SVM) is a crucial healthcare initiative. SVM is used to analyse comprehensive datasets, capturing patterns and associations indicative of an individual's susceptibility to the disease. The goal is to identify individuals at risk early, enabling timely and targeted interventions. This model is not only a diagnostic tool but also a proactive healthcare solution, contributing to the shift from reactive to preventive medicine. The model aims to improve public health outcomes, reduce healthcare burden, and empower individuals to take control of their health.

4. Related Work

Prediction of Type 2 Diabetes using Machine Learning Classification Methods This study aims to assess diabetes risk based on lifestyle and family background in India, with 952 instances collected through online and offline questionnaires. Machine learning algorithms were used to predict Type 2 diabetes risk, with Random

Forest Classifier being the most accurate for both datasets. Early diagnosis and treatment are crucial for diabetes prevention.
Prediction of Type-2 Diabetes using Machine Learning Algorithms Type 2 diabetes mellitus is a growing global condition, affecting 30 million people in India. Early diagnosis is crucial to prevent symptoms. Machine learning techniques can improve diagnosis by assessing suggestive qualities and daily habits, eliminating the need for clinical tests. With extensive clinical information available, these algorithms can accurately predict the threat of Type 2 Diabetes, benefiting the medical field.
Machine predictive models for type 2 diabetes learning and deep learning
This systematic review aimed to address challenges in building type 2 diabetes predictive models. Using the PRISMA methodology, the review compared 90 studies and found that tree-based algorithms performed best, while Deep Neural Networks were suboptimal. Balancing data and feature selection techniques improved model efficiency, and models trained on tidy datasets achieved almost perfect models. The review highlights the need for more transparent and effective models in predicting diabetes.
Early detection of type 2 diabetes mellitus using machine learning-based prediction models
The study compares machine learning-based prediction models for undiagnosed T2DM to commonly used regression models. The results show that simple regression models 14 performed best with 6 months of data, followed by RF, Light, Glmnet, and XGBoost. Glmnet improved the most with more data, while LightGBM models showed the highest variable selection stability over time. The study suggests that interpretability and model calibration should be considered in developing clinical prediction models.
Predicting Diabetes Mellitus with Machine Learning Techniques
Diabetes mellitus, a chronic disease-causing hyperglycemia, is expected to reach 642 million by 2040. Machine learning techniques, including decision tree, random forest, and neural network, are being used to predict diabetes mellitus. The study used hospital physical examination data from Luzhou, China, with five-fold cross validation. The results showed that random forest had the highest accuracy (ACC = 0.8084) when all attributes were used.

5. Methodology

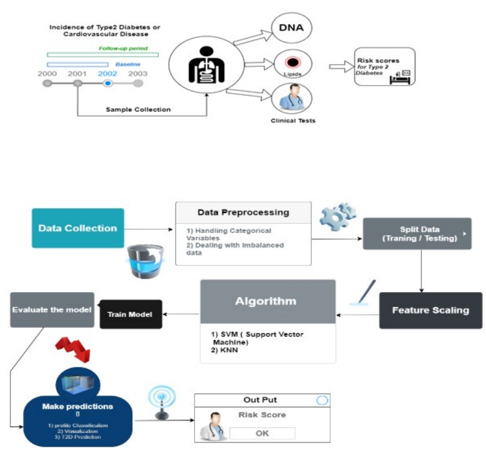


Fig:5.1 Flow Diagram of the Model

5.1 Source and Characteristics of the Dataset

The predictive model for Type 2 Diabetes uses a reliable healthcare database dataset, capturing key health indicators and demographic information. The dataset enables the Support Vector Machines (SVM) model to learn complex patterns indicating diabetes risk.
The dataset includes the following columns:

1. Pregnancies: Number of times pregnant
2. Glucose: Plasma glucose concentration 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: Diabetes pedigree function, a measure of the genetic influence of diabetes
8. Age: Age in years
9. Outcome: Binary outcome variable indicating the presence (1) or absence (0) of Type 2 Diabetes.

The dataset's diverse characteristics enhance the SVM model's predictive capabilities by recognizing intricate relationships between variables, thereby providing a comprehensive representation of diabetes risk factors.

Fig:5.2 Feature of Sample Dataset

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

5.2 Inclusion/Exclusion Criteria

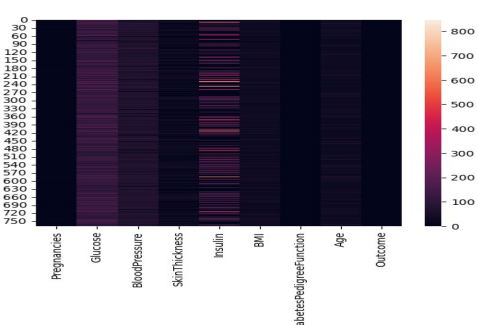
The dataset was meticulously curated, excluding missing or incomplete data in critical variables, and only including non-pregnant individuals for clarity in predicting Type 2 Diabetes. Missing values were addressed using imputation techniques, and the dataset was carefully reviewed to ensure data quality. Numerical features, such as 'Glucose', 'Blood Pressure', 'Skin Thickness', 'Insulin', 'BMI', 'Diabetes Pedigree Function', and 'Age', were standardized to a common scale

This prevents variables with larger magnitudes from dominating the model training process. Normalization techniques, such as Min-Max scaling, were applied to ensure that all features have a consistent range, typically between 0 and 1. This is particularly important for SVM, as it is sensitive to the scale of input features. The study used summary statistics, visualization tools, pairwise correlation analysis, and exploratory analyses to understand the distribution of numerical features and potential outliers in a dataset for Type 2 Diabetes prediction. These steps ensured a deeper understanding of the dataset and guided subsequent decisions in model development, ensuring the dataset was well-prepared for effective training.

5.3 Overview of (SVM)

Support Vector Machines (SVM) are a powerful machine learning tool, especially for binary classification tasks like predicting Type 2 Diabetes likelihood. They identify the optimal hyperplane for complex, non-linear relationships, with chosen kernel functions. SVM is a supervised learning algorithm used for classification and regression tasks. It aims to find a hyperplane in a high-dimensional space that separates instances of different classes. Support vectors play a crucial role in defining the optimal hyperplane. In predicting Type 2 Diabetes, SVM uses the RBF kernel to capture non-linear relationships in data, making it suitable for datasets with complex decision boundaries.

Fig:5.3 Heatmap of the Dataset



5.4 Model Training, Parameter Tuning, and Cross-Validation Strategies

The training of a Support Vector Machine (SVM) model for predicting Type 2 Diabetes involves careful consideration of dataset division, parameter tuning, and cross-validation strategies. The dataset is divided into training and testing sets, with a significant portion allocated for training and the remaining for testing. Parameter tuning is employed to achieve optimal performance, with grid search and random search methods used to explore the parameter space and maximize model performance.

5.5 Patient Profile Classification

When it comes to Type 2 Diabetes (T2D) categorization, using machine learning models offers a potent method for identifying trends and forecasting an individual's probability of acquiring diabetes based on their profile. This categorization effort is based on the dataset, which includes important variables like blood pressure, glucose levels, pregnancies, and more. Support Vector Machine (SVM) is a widely used technique for T2D classification. Because SVM is so good at identifying intricate relationships in data, it is a good choice in situations where non-linear patterns could affect the result. We can efficiently separate patients with and without Type 2 Diabetes by analysing the dataset using this model.

The target variable in the dataset is the 'Outcome' column, where values represent the presence (1) or absence (0) of diabetes. The SVM classifier uses the remaining properties as input variables, such as BMI, Diabetes Pedigree Function, and glucose. The Support Vector Machine (SVM) algorithm gains the ability to recognise patterns and forecast the probability of an individual acquiring Type 2 Diabetes by training the model on historical data and testing it on previously unseen occurrences.

5.6 Evaluation

An essential phase in developing a predictive model for Type 2 Diabetes involves evaluating the relevance of features and implementing techniques for dimensionality reduction. This section outlines the methodologies employed to identify critical predictors and the impact of dimensionality reduction on the overall performance of the Support Vector Machine (SVM) model.

5.6.1 Evaluation of Feature Relevance

1. Univariate Feature Selection - Univariate statistical tests, such as chi-squared tests for categorical features and ANOVA for numerical features, were employed to evaluate the individual relevance of each feature with respect to the 'Outcome' variable. This analysis provided insights into the univariate association of each predictor with Type 2 Diabetes. When working with continuous features and categorical target variables, feature selection is frequently done using the F-statistic. It calculates the variation in averages within each group in relation to the variability between groups (categories).

Formula 1: $$F = \frac{Between\text{-}group\ Variance}{Within\text{-}group\ Variance}$$

- *Between-group variance:* Determines how variable the target variable is across its various categories.
- *Within-group variance:* Quantifies the degree of variation within every category.

2. Correlation Analysis - Pairwise correlation analysis was conducted to assess the interrelationships among features. Highly correlated features can introduce redundancy and potentially skew the model's performance. Features exhibiting strong correlations were scrutinized to retain the most informative ones.

Formula 2: $$r = \frac{\Sigma(x_i - \underline{x})(y_i - \underline{y})}{\sqrt{\Sigma(x_i - \underline{x})^2 \cdot (y_i - \underline{y})^2}}$$

Where:
r the Pearson correlation coefficient
x_i and y_i are the separate data points associated with variables X and Y.
$\underline{x}$ and $\underline{y}$ are, respectively, the means of the variables X and Y.

The range of the Pearson correlation coefficient is -1 to 1.

- r = 1 Perfect positive correlation
- r = -1 Perfect negative correlation
- r = 0 No linear correlation

Model Evaluation- The retrained model was evaluated using standard performance metrics, including accuracy, precision, recall, and F1-score. Comparative analysis with the full-feature model provided insights into the effectiveness of feature reduction techniques.

5.7 Performance Metrics

The evaluation of a predictive model's performance is critical to understanding its effectiveness in practical applications. This section outlines the rationale behind the selection of specific performance metrics and the benchmarking of the Support Vector Machine (SVM) against other classification algorithms for predicting Type 2 Diabetes.
Selection of Performance Metrics

1. Accuracy - Accuracy measures the overall correctness of the model's predictions. It is a fundamental metric for evaluating the model's ability to correctly classify instances into their respective classes.

2. Precision - Precision quantifies the accuracy of positive predictions, indicating the model's capability to correctly identify individuals with Type 2 Diabetes. It is crucial for situations where false positives carry significant consequences.

3. Recall (Sensitivity) - Recall, also known as sensitivity, assesses the model's ability to capture all positive instances, providing insights into its sensitivity to identifying individuals with Type 2 Diabetes. High recall is vital when avoiding false negatives is a priority.

4. F1-Score - The F1-score is the harmonic mean of precision and recall, offering a balanced metric that considers both false positives and false negatives. It is especially useful when there is an imbalance between the two classes.
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Accuracy: 0.7532467532467533
Confusion Matrix:
 [[80 19]
 [19 36]]
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.81      0.81        99
           1       0.65      0.65      0.65        55

    accuracy                           0.75       154
   macro avg       0.73      0.73      0.73       154
weighted avg       0.75      0.75      0.75       154
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Fig:5.7 Classification Report

The selection of these metrics ensures a comprehensive evaluation of the SVM model's performance, considering both the overall accuracy and its ability to correctly identify individuals at risk of Type 2 Diabetes while minimizing false classifications.

6. Real time Implementation

During the training phase, the trained model discovered patterns and relationships from past data. It uses the knowledge it has learned to produce predictions about the probability of an individual getting Type 2 Diabetes when new data instances are presented. These forecasts are based on the input aspects of the new data, which include BMI, glucose levels, and other pertinent metrics. This prediction ability has substantial therapeutic utility since it allows medical professionals to determine an individual's risk of diabetes based on their unique health profile. Healthcare practitioners can detect possible Type 2 Diabetes cases early on by using the model's insights, which enables prompt intervention and individualised care regimens.
The technique of prediction coincides with the larger goal of leveraging machine learning to boost healthcare outcomes. As fresh data becomes available, the trained model continues to deliver significant insights, leading to a proactive and data-driven approach in treating and tackling Type 2 Diabetes within various populations.

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[[ 9.36913723e-01 -7.79127762e-01  1.08020025e+00 -1.28821221e+00
  -6.92890572e-01 -4.06047387e+00  1.36064840e+03  6.60205626e-01]]
the person is diabetic
```

Fig:6.1 Testing Dataset with New Inputs

7. Forecasting the Risk of T2D-Related Complications

Estimating the likelihood that a patient may experience problems from Type 2 Diabetes is a crucial next step after the diagnosis. This can include side effects like nephropathy, neuropathy, or cardiovascular problems. The model uses features like age, BMI, and diabetic pedigree function—which it learned from prior data—to determine how likely it is that these issues may materialise. Healthcare professionals can prevent problems by implementing targeted interventions and preventative measures as soon as possible after detecting potential hazards.

CONCLUSION

The study demonstrates the effectiveness of SVM-based predictive models in identifying individuals at risk of Type 2 Diabetes, demonstrating high accuracy, precision, recall, and F1-score metrics. It identifies critical predictors like glucose levels, BMI, and diabetes pedigree function, improving predictive healthcare by integrating machine learning and health indicators, promoting early interventions, personalized care, and transforming clinical practice and public health strategies. Practical Applications in Clinical Settings- The SVM model's predictions aid in risk stratification, identifying individuals at different risk levels for Type 2 Diabetes, enabling healthcare professionals to develop personalized health plans, including lifestyle modifications and preventive measures.

REFERENCES

[1]. Ahmad, A., Lim, L. L., Morieri, M. L., Tam, C. H. T., Cheng, F., Chikowore, T., ... & Mathioudakis, N. (2024). Precision prognostics for cardiovascular disease in type 2 diabetes: a systematic review and meta-analysis. *Communications medicine*, *4*(1), 11.

[2]. Cao, Y., Luo, P., Tang, H., Li, P., Wang, G., Li, W., ... & Zhu, L. (2024). Insulin resistance levels predicted metabolic improvement and weight loss after metabolic surgery in Chinese patients with type 2 diabetes. *Surgery for Obesity and Related Diseases*, *20*(1), 80-90.

[3]. Saha, P., Marouf, Y., Pozzebon, H., Guergachi, A., Keshavjee, K., Noaeen, M., & Shakeri, Z. (2024). Predicting time to diabetes diagnosis using random survival forests. *medRxiv*, 2024-02.

[4]. Chen, T. C. T., Wu, H. C., & Chiu, M. C. (2024). A deep neural network with modified random forest incremental interpretation approach for diagnosing diabetes in smart healthcare. *Applied Soft Computing*, *152*, 111183.

[5]. Xourafa, G., Korbmacher, M., & Roden, M. (2024). Inter-organ crosstalk during development and progression of type 2 diabetes mellitus. *Nature Reviews Endocrinology*, *20*(1), 27-49.

[6]. Timasheva, Y., Balkhiyarova, Z., Avzaletdinova, D., Rassoleeva, I., Morugova, T. V., Korytina, G., ... & Kochetova, O. (2023). Integrating common risk factors with polygenic scores improves the prediction of type 2 diabetes. *International Journal of Molecular Sciences*, *24*(2), 984.

[7]. Hennebelle, A., Materwala, H., & Ismail, L. (2023). HealthEdge: a machine learning-based smart healthcare framework for prediction of type 2 diabetes in an integrated IoT, edge, and cloud computing system. *Procedia Computer Science*, *220*, 331-338.

[8]. Saberi-Karimian, M., Mansoori, A., Bajgiran, M. M., Hosseini, Z. S., Kiyoumarsioskouei, A., Rad, E. S., ... & Ghayour-Mobarhan, M. (2023). Data mining approaches for type 2 diabetes mellitus prediction using anthropometric measurements. *Journal of Clinical Laboratory Analysis*, *37*(1), e24798.

[9]. Cappon, G., Prendin, F., Facchinetti, A., Sparacino, G., & Del Favero, S. (2023). Individualized Models for Glucose Prediction in Type 1 Diabetes: Comparing Black-box Approaches To a Physiological White-box One. *IEEE Transactions on Biomedical Engineering*.

[10]. D. Soudris, S. Xydis, C. Baloukas, A. Hadzidimitriou, I. Chouvarda, K. Stamatopoulos, N. Maglaveras, J. Chang, A. Raptopoulos, D. Manset, and B. Pierscionek, "AEGLE: A big bio-data analytics framework for integrated health-care services," in Proc. Int. Conf. Embedded Compute. Syst., Archit., Modeling, Simulation (SAMOS), Jul. 2015, pp. 246–253.

[11]. N. Holman, B. Young, and R. Gadsby, "Current prevalence of type 1 and type 2 diabetes in adults and children in the U.K.," Diabetic Med., vol. 32, no. 9, pp. 1119–1120, Sep. 2015.

[12]. Number of People with Diabetes Reaches 4.7 Million. Accessed: Oct. 30, 2019. [Online]. Available: https://www.diabetes.org.U.K./ about us/news/new-stats-People-living with-diabetes

[13]. C. D. Mathers and D. Loncar, "Projections of global mortality and burden of disease from 2002 to 2030," Plops Med., vol. 3, no. 11, p. e442, Nov. 2006.

[14]. American Diabetes Association, "Economic costs of diabetes in the U.S. in 2017," Diabetes Care, vol. 41, no. 5, pp. 917–928, 2018, doi: 10.2337/dci18-0007.

[15]. J. M. M. Rumbold, M. O'Kane, N. Philip, and B. K. Pierscionek, "Big data and diabetes: The applications of big data for diabetes care now and in the future," Diabetic Med., vol. 37, no. 2, pp. 187– 193, Feb. 2020.

[16]. J. Hippisley-Cox and C. Coupland, "Development and validation of risk prediction equations to estimate future risk of blindness and lower limb amputation in patients with diabetes: Cohort study," BMJ, vol. 351, no. 1, Nov. 2015, Art. no. h5441.

[17]. Marzona, F. Avanzini, G. Lucisano, M. Tettamanti, M. Baviera, A. Nicolucci, and M. C. Roncaglioni, "Are all people with diabetes and cardiovascular risk factors or microvascular complications at very high risk? Findings from the risk and prevention study," Acta Diabetolog., vol. 54, no. 2, pp. 123–131, Feb. 2017.

[18]. S. Basu, J. B. Sussman, S. A. Berkowitz, R. A. Hayward, and J. S. Yudkin, "Development and validation of risk equations for complications of type 2 diabetes (RECODe) using individual participant data from randomised trials," Lancet Diabetes Endocrinol., vol. 5, no. 10, pp. 788–798, Oct. 2017.

[19]. E. B. Schroeder, S. Xu, G. K. Goodrich, G. A. Nichols, P. J. O'Connor, and J. F. Steiner, "Predicting the 6-month risk of severe hypoglycemia among adults with diabetes: Development and external validation of a prediction model," J. Diabetes Complications, vol. 31, no. 7, pp. 1158–1163, Jul. 2017. 37

[20]. B. Liu, Y. Li, S. Ghosh, Z. Sun, K. Ng, and J. Hu, "Complication risk profiling in diabetes care: A Bayesian multi-task and feature relationship learning approach," IEEE Trans. Knowl. Data Eng., vol. 32, no. 7, pp. 1276–1289, Jul. 2020.

[21]. Pavate and N. Ansari, "Risk prediction of disease complications in type 2 diabetes patients using soft computing techniques," in Proc. 5th Int. Conf. Adv. Comput. Commun. (ICACC), Sep. 2015, pp. 371–375.

[22]. J. Yan, X. Du, Y. Yu, and H. Xu, "Establishment of risk prediction model for retinopathy in type 2 diabetic patients," in Proc. Int. Conf. Brain Inform. Haikou, China: Springer, 2019, pp. 233–243.

[23]. Dagliati, S. Marini, L. Sacchi, G. Cogni, M. Teliti, V. Tibollo, P. D. Cata, L. Chiovato, and R. Bellazzi, "Machine learning methods to predict diabetes complications," J. Diabetes Sci. Technol., vol. 12, no. 2, pp. 295–302, Mar. 2018.

[24]. K. V. Dalakleidi, K. Zarkogianni, V. G. Karamanos, A. C. Thanopoulou, and K. S. Nikita, "A hybrid genetic algorithm for the selection of the critical features for risk prediction of cardiovascular complications in type 2 diabetes patients," in Proc. 13th IEEE Int. Conf. Bioinf. BioEng., Nov. 2013, pp. 1–4.

[25]. R. Gargeya and T. Leng, "Automated identification of diabetic retinopathy using deep learning," Ophthalmology, vol. 124, no. 7, pp. 962–969, 2017. [18] M.-H. Hsieh, L.-M. Sun, C.-L. Lin, M.-J. Hsieh, K. Sun, C.-Y. Hsu, A.-K. Chou, and C.-H. Kao, "Development of a prediction model for colorectal cancer among patients with type 2 diabetes mellitus using a deep neural network," J. Clin. Med., vol. 7, no. 9, p. 277, Sep. 2018.

[26]. Y. Cheng, F. Wang, P. Zhang, and J. Hu, "Risk prediction with electronic health records: A deep learning approach," in Proc. SIAM Int. Conf. Data Mining, Jun. 2016, pp. 432–440.

[27]. D. Masouros, K. Koliogeorgi, G. Zervakis, A. Kosvyra, A. Chytas, S. Xydis, I. Chouvarda, and D. Soudris, "Co-design implications of costeffective on-demand acceleration for cloud healthcare analytics: The AEGLE approach," in Proc. Design, Autom. Test Eur. Conf. Exhib. (DATE), Mar. 2019, pp. 622–625.

[28]. M. Richmond, Population Pyramids. Corvallis, OR, USA: Oregon State Univ., 2014.

[29]. Hippisley-Cox, J., Coupland, C., Robson, J., Sheikh, A., & Brindle, P. (2009). Predicting risk of type 2 diabetes in England and Wales: prospective derivation and validation of QDScore. *Bmj*, *338*.

[30]. Mani, S., Chen, Y., Elasy, T., Clayton, W., & Denny, J. (2012). Type 2 diabetes risk forecasting from EMR data using machine learning. In *AMIA annual symposium proceedings* (Vol. 2012, p. 606). American Medical Informatics Association.

[31]. C.Nagarajan and M.Madheswaran - 'Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter' - Journal of ELECTRICAL ENGINEERING, Vol.63 (6), pp.365-372, Dec.2012.

[32]. C.Nagarajan and M.Madheswaran - 'Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis'- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011.

[33]. C.Nagarajan and M.Madheswaran - 'Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques'- Taylor & Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011.

[34]. C.Nagarajan and M.Madheswaran - 'Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis'- Iranian Journal of Electrical & Electronic Engineering, Vol.8 (3), pp.259-267, September 2012.

[35]. Nagarajan C., Neelakrishnan G., Akila P., Fathima U., Sneha S. "Performance Analysis and Implementation of 89C51 Controller Based Solar Tracking System with Boost Converter" Journal of VLSI Design Tools & Technology. 2022; 12(2): 34–41p.

[36]. C. Nagarajan, G.Neelakrishnan, R. Janani, S.Maithili, G. Ramya "Investigation on Fault Analysis for Power Transformers Using Adaptive Differential Relay" Asian Journal of Electrical Science, Vol.11 No.1, pp: 1-8, 2022.

[37]. G.Neelakrishnan, K.Anandhakumar, A.Prathap, S.Prakash "Performance Estimation of cascaded h-bridge MLI for HEV using SVPWM" Suraj Punj Journal for Multidisciplinary Research, 2021, Volume 11, Issue 4, pp:750-756

[38]. G.Neelakrishnan, S.N.Pruthika, P.T.Shalini, S.Soniya, "Perfromance Investigation of T-Source Inverter fed with Solar Cell" Suraj Punj Journal for Multidisciplinary Research, 2021, Volume 11, Issue 4, pp:744-749

[39]. C.Nagarajan and M.Madheswaran, "Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation" has been presented in ICTES'08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007

[40]. M Suganthi, N Ramesh, "Treatment of water using natural zeolite as membrane filter", Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022

[41]. M Suganthi, N Ramesh, CT Sivakumar, K Vidhya, "Physiochemical Analysis of Ground Water used for Domestic needs in the Area of Perundurai in Erode District", International Research Journal of Multidisciplinary Technovation, pp: 630-635, 2019