Grenze International Journal of Engineering and Technology, June Issue

Prediction of Stress and Diabetic Retinopathy using Touch Screen Data

Dr. Sunil Bhutada[1], Dr. V. Kakulapati[2], Sai Vignesh Kondi[3], Manoj Reddy Dareddy[4] and Lokesh Madishetty[5]
[1-5]Sreenidhi Institute of Science and Technology, Yamnampet, Ghatkesar, Hyderabad, Telangana-501301.
Email: sunilb@sreenidhi.edu.in, vldms@yahoo.com, saivigneshkondi@gmail.com, dareddymanoj1234@gmail.com, lokesh.madishetty@gmail.com

***Abstract*— The sensitivity of the display screen to human touch enables the ability to interact with a computer by touching images or text on a touch screen. Extended use of touch displays, particularly in incorrect ergonomic postures, may result in complications such as ocular fatigue, repetitive strain injuries, and diabetic retinopathy. Diabetes-related retinal damage (DR) is a condition that affects the eyes specifically and has the potential to impair vision. Stress is a psychological factor that can influence the onset and progression of diabetes and its complications. Touch screen data refers to the information collected from the interactions of users with touch-enabled devices, such as smartphones or tablets. Touch screen data can provide insights into the user's behavior, mood, cognition, and health status. One of the new global concerns to public health is diabetes. Depending on the ophthalmologist's experience, the diagnostic process can be difficult or time-consuming, especially in environments with limited resources. Automated techniques are currently used to classify cases of Diabetes Retinopathy (DR). Tens of millions of individuals suffer from depression each year, yet only a small percentage of them get timely treatment. Therefore, it is essential to automatically identify human tension and relaxation using social media promptly. Early detection and effective management of stress are crucial in preventing its escalation into a severe condition. This paper presents a method to predict expressions of stress and Diabetic retinopathy by using ML techniques LR (logistic regression), RF (random forest), and XG boost methods to detect the correlation between stress and diabetes while using touch screen.**

***Index Terms*— diabetes, eyesight, Stress, Prediction, Feature Extraction, ML, techniques, correlation, touch, screen.**

I. INTRODUCTION

The growing use of digital gadgets has detrimental effects on both physical and mental well-being. Prolonged and consistent exposure may heighten stress levels, provoke anxiety, and disrupt sleep patterns, ultimately resulting in obesity, cardiovascular ailments, hypertension, impaired stress control, reduced levels of HDL cholesterol, and insulin resistance. Psychological consequences include suicide ideation, depressive symptoms, impaired sleep, and negativity impacted by content. Relying on digital devices may lead to heightened arousal, elevated levels of stress hormones, and impede mental vitality and growth [1].
Stress may induce insulin resistance, resulting in elevated blood sugar levels, a medical condition referred to as hyperglycemia. This may heighten the susceptibility to diabetic problems and impact mood and self-care. The

Grenze ID: 01.GIJET.10.2.511_1

diagnosis of diabetes may induce stress, particularly during the first stages, due to the need for meticulous dietary management and the acquisition of new knowledge. Regular monitoring of blood sugar levels and administering injections may induce stress, as can the worry associated with hypoglycemia. However, this anxiety can be effectively addressed by taking measures to prevent low blood sugar levels. Certain individuals may have sensations of being overwhelmed and distressed because of diabetes, harboring concerns about potential consequences and feelings of guilt if their diabetes care deviates from the desired course. Diabetes distress is a prevalent symptom that must be well managed to avoid fatigue [2].

Utilizing cellular telephones is to develop cost-effective, energy-efficient retina imaging devices for testing and automatic identification of diabetic retinal disease. The excessive and repeated use of touch screens might lead to notable issues, such as discomfort related to ergonomics or musculoskeletal illnesses. The association between anxiety and addiction to screens revolves around the specific patterns of usage of screens in response to different sources of stress. This statement highlights the complex relationship between addiction, stress, and screen usage. It underscores the need to thoroughly study how an individual's perception of screen addiction, various types of stress, and habits of usage of screens are interconnected [3]

Studies suggest that stress may result in emotional or physical problems as a result of how it is perceived, evaluated, and influenced by both internal and external variables. Displays, serving as means of communication, can modify these processes via the use of messaging. In order to properly handle stress, people need to actively modify their perception and evaluation of situations. Stress adaptation is a contextual process in which people use a combination of avoidance-approach and problem-focused coping techniques, depending on their previous experiences and resilience characteristics. Contemporary displays are widely favored as sources of amusement and knowledge, offering diversions, relaxation, and techniques for dealing with information and problem-solving. The current displays, with their informatics and hypertextual characteristics, enable users to customize them based on their cultural or psychological requirements. Mobile and internet-connected displays can overcome time and space limitations, allowing for more social and professional assistance.

Metabolic disorder function is greatly affected by stress, and both psychological and physical stress may trigger the onset of diabetes. The neuroendocrine framework, including both the central and peripheral nerve systems, is implicated. Psychological stress elevates levels of catecholamine and glucocorticoids, which in turn raises the need for insulin and leads to insulin resistance. Stress might contribute to insulin resistance and the development of diabetes in individuals with diabetes, resulting in persistent high blood sugar levels [4].

This work used machine learning algorithms to forecast the occurrence of diabetes associated with stress in individuals who use touch screens. In this work, three models, namely RF (Random Forest), LR (Logistic Regression), and XG Boosting, were evaluated. The algorithms were trained using two datasets, which included measurements of glucose, insulin, blood pressure, BMI, stress, and age. The algorithms' accuracy was evaluated using performance measures. Users may retrieve the information to anticipate stress and diabetes by using touch-screen devices.

The remainder of the present study is as: Section 2 delves into the background of the proposed method and Section 3 explores related methods in correlation between stress and diabetes. In 4 discusses the framework of the proposed method, whereas Section 5 discusses implementation analysis followed by the discussion of the proposed system in Section 6. Section 7 concludes with remarks followed by a discussion of future research directions.

II. BACKGROUND

Prolonged usage of computer screens may result in many negative effects such as migraines, tiredness of the eyelids, reduced visual acuity, eye irritation, and discomfort caused by glare, insufficient lighting, or improper viewing angles.

Touchscreen mobile phones do not provide any substantial risk as a result of the magnetic field produced by high-frequency carriers. Nevertheless, the magnitude and intensity of the field are negligible in comparison to the carrier frequency. When using touch screen phones, the likelihood of developing eye vision issues is higher owing to the smaller displays in comparison to computer screens. This raises the chances of straining the eyes when reading texts [5].

The prevalence of diabetes is increasing worldwide, with a projected rate of 7,079 cases per 100,000 inhabitants by the year 2030. This may be partially due to the widespread adoption of sedentary behaviors and the increasing dependence on cellular phones, television, and laptops. Cell phones play a crucial role in facilitating payments via mobile devices in China. Based on the NHN (National Health and Nutrition) Examination Survey, over 50% of the estimated time is spent on passive behaviors. The World Health Organization has released a new directive aimed at reducing sedentary habits.

Deterioration of the retina's blood vessels leads to diabetic retinopathy, which manifests as fluid leakage, bleeding, and the development of new, more delicate blood vessels. Initially, it may result in minor visual impairments but may lead to complete loss of eyesight [8].

Stress has an impact on how people use smartphones, and researchers have used non-invasive techniques such as analyzing call records, SMS logs, app usage, battery consumption, screen on-off patterns, internet surfing, and Bluetooth proximity to identify stress [9].

Multiple research studies have examined the identification of diabetes.ML methods currently exist. A proposal was made to forecast diabetes utilizing algorithms such as k-NN(k-nearest Neighbor), k-means, and segment and restricted method. A simple dataset about diabetes is selected for conducting the comparison study. This text discusses the significance of feature analysis in using ML approaches for forecasting mellitus.

III. RELATED WORK

An evaluation was carried out to assess the image quality of retinal imaging devices that are based on smartphones, including iExaminer, D-Eye, Peek Retina, and iNview. Utilizing a deep learning architecture, the study concluded that iNview exhibited an enormous field perspective and exceptional image clarity. The assessment precision for iExaminer, D-Eye, Peek Retina, and iNview photos were 61%, 62%, 69%, and 75%, correspondingly. Nevertheless, the efficacy of detecting diabetic retinopathy in the network declined as the field of vision decreased. The research proposes that smartphone-based retinal imaging devices may serve as a substitute for direct ophthalmoscopes. However, it emphasizes that the field of vision plays a critical role in ensuring accurate automated identification [10].

The study investigates stress detection via keyboard dynamics, a subject that has been investigated in several investigations. A study on human behavior regarding smartphone touch interfaces to comprehend emotional states [11]. The study in question gathered and examined user-generated data from a variety of sensors. In another investigation, finger-strokes were captured during an iPod game and specific forces were examined [12]. The method involves using keyboard dynamics to detect tension and identify variations in stress levels via these patterns [13]. An automated emotion detection system was created [14] by using the modeling of spelling features and emotion persistence.

Investigators have shown a correlation between anxiety and the onset of type 1 diabetes. It is hypothesized that stress may lead to the demise of β-cells in those who have an inherited susceptibility to autoimmunity. Nevertheless, extensive studies have failed to establish an association between adverse conditions and the occurrence of diabetes [15]. Another study [16] found no association between stressful situations and the onset of type 1 diabetes. Nevertheless, notable variations in life changes and social supports, particularly during adolescence, could have concealed any connection between traumatic events and the occurrence of mellitus.

IV. METHODOLOGY

The Study aims to predict the presence of diabetes and stress using machine learning models. It employs data visualization, feature analysis, and multiple classifiers to build predictive models and assess their performance.

Data is collected from freely available Kaggle and two datasets based on stress and diabetic retina therapy can use various sensors and devices to collect touch screen data from users, such as the frequency, duration, intensity, location, direction, speed, patterns, errors, corrections, usage, and context of touch interactions. Based on common columns the two data sets are integrated and finally, the data set looks as follows.

TABLE I: AFTER INTEGRATION OF TWO DATA SETS, THE DATA SET LOOKS LIKE

Age	Patient ID	Diastolic BP	SerumInsulin	Body Mass Index
21	1.627627e+06	66.821429	141.571429	32.971550
22	1.618850e+06	64.761905	140.428571	34.448402
23	1.552299e+06	74.450000	84.250000	29.656094
24	1.512709e+06	65.250000	103.750000	35.617206
25	1.404148e+06	67.583333	98.666667	26.658906
26	1.587481e+06	64.000000	83.428571	26.391497
29	1.404894e+06	70.000000	59.000000	48.440163
31	1.480060e+06	66.000000	45.500000	18.850191

Data preprocessing: perform various operations to clean, transform, and integrate the data, such as feature scaling, imputation, selection, and augmentation. The framework can also perform data analysis and visualization to explore and understand the data, such as descriptive statistics, correlation analysis, and clustering.
Data modeling: can apply different machine learning and deep learning techniques to build and evaluate predictive models, such as LR, RF, and XGBoost.
Data loading and Exploration: Displays basic information about the dataset and explores the target variables ('Diabetes', 'Stress').
Data Visualization: Uses various visualization techniques like histograms, pair plots, heatmaps, etc., to understand the distribution, relationships, and correlations among features and target variables.
Features Extraction and Model Building: Prepares the data by separating features (X) and target variables (Y) for both 'Diabetes' and 'Stress' predictions.
Logistic Regression: It determines the optimal coefficients for a linear model by examining the connection between a dependent variable with a binary value and more than one independent variable. It provides a straightforward prediction approach and baseline accuracy scores, allowing for comparison with other non-parametric machine learning models [17].
XG Boost: It is a prominent gradient-boosting approach that includes regularization, the approach involves using a weighted percentile sketch, which is a block pattern designed for concurrent processing. It also incorporates cache monitoring and out-of-core computational power. It provides the ability to manage to overfit, effectively handles datasets with sparse data, streamlines the process of scaling on computers with many cores, and minimizes memory use while training huge datasets [18].
Random Forest: To mitigate the negative effects of high variance, RF utilizes an ensemble model that employs several random decision trees for categorization. This approach takes into consideration the average forecast among the trees. Decisions are determined by considering the level of impurity and the amount of information gained [19].

V. IMPLEMENTATION ANALYSIS

The model assesses the feature importance using the Extra Trees Classifier to understand significant predictors.
Model Evaluation: the data set is split into training and testing sets and evaluates the model’s performance

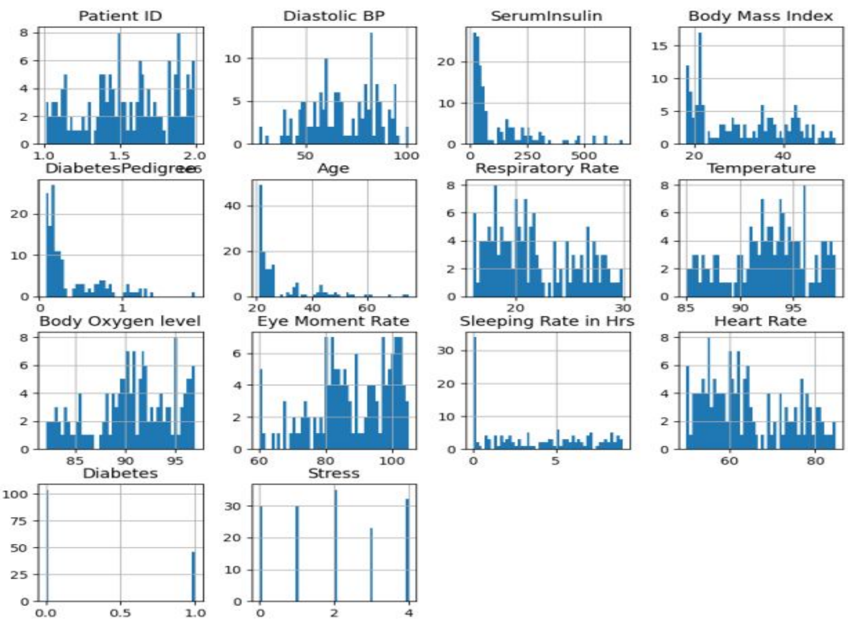
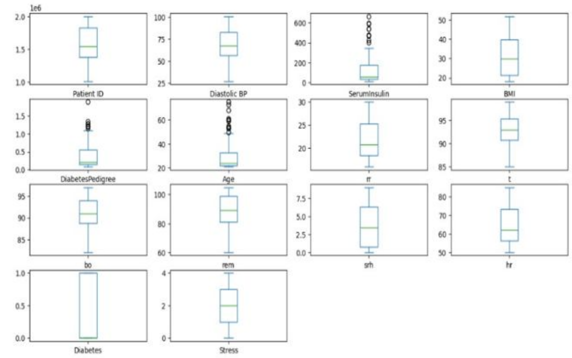


Fig 1: The Histogram analysis of the data set contains different attributes

Displays the accuracy scores achieved by each model for predicting 'Diabetes' and 'Stress'.
Generates results Dataframe showcasing the accuracy scores for each model.
Ranks the models based on their performance scores



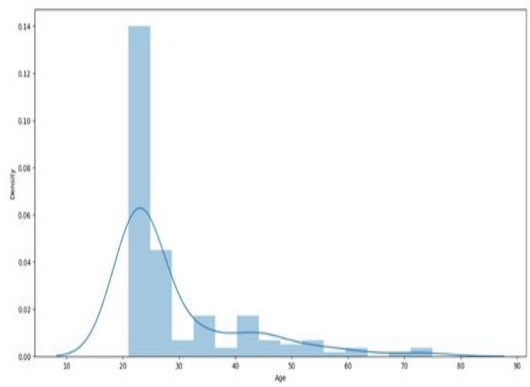


Fig 2: The feature extraction of data set attributes

Fig 3: The correlation between stress and diabetes using logistic regression

Logistic accuracy: 76%

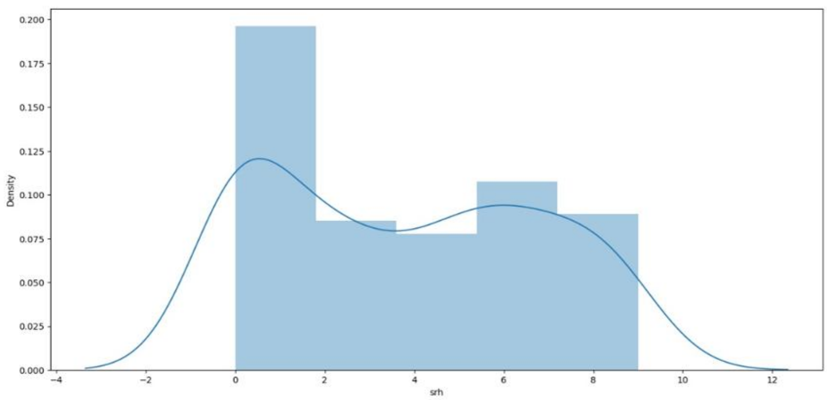


Fig 3: The correlation between stress and diabetes using Random Forest

Random forest accuracy: 86%

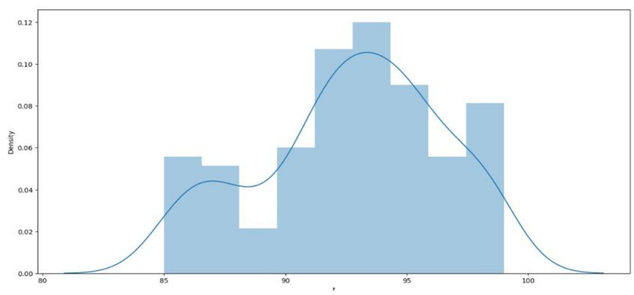


Fig 4: The correlation between stress and diabetes using XG boost

XG boost accuracy: 90%

VI. Discussion

Prolonged exposure to screens, whether for leisure or work purposes, may lead to permanent injury in humans. Research indicates the negative effects of stress-related diabetes. Furthermore, with the progress of technology, people are becoming more immersed in the digital realm without their explicit agreement. Collecting and organizing more touch screen data from users with diabetes and DR, as well as their clinical and psychological assessments, to create a large and diverse dataset for training and testing the predictive models.

Exploring and extracting more features from touch screen data that are relevant and informative for predicting stress and DR, such as the frequency, duration, intensity, location, direction, speed, patterns, errors, corrections, usage, and context of touch interactions. Performance analysis is to evaluate the predictive models, such as LR, RF, and XGBoost. Enhance the precision, resilience, comprehensibility, and applicability of the predictive models via the use of suitable techniques for selecting features, reducing dimensionality, applying regularization, optimizing performance, validating results, and visualizing data. Developing and deploying user-friendly and secure applications or devices that can collect and analyze touchscreen data in real-time and provide feedback or intervention to the users based on their stress and DR status

VII. CONCLUSION

Detecting human tension as well as relaxation automatically via the correlation between stress and diabetic retinopathy by analyzing touch screen use is of utmost importance. Detecting and managing stress and diabetic retinopathy early on is crucial in order to prevent the development of serious complications. This paper describes an approach to predict stress using the information from the data set which is using in this study. This paper predicts stress and diabetes while using touch screens by applying different machine-learning techniques. In this work, machine learning techniques logistic regression, XG boost, and random forest algorithms were used to predict stress and diabetes using the touch screen. The result will give accurate results on how humans suffer from working prolonged hours with touch screens. The study systematically explores data, builds multiple predictive models, and assesses their accuracy for predicting diabetes and stress. The logistic regression predicts that people experience stress while using the touch screen for prolonged hours which leads to chronic diabate retinotherapy. The best-performing models are XGBoost and Random Forest for both 'Diabetes' and 'Stress' predictions, exhibiting accuracy scores of 0.9 and 0.86, respectively.

FUTURE ENHANCEMENT

The release of stress-induced hormones may lead to elevated blood sugar levels, potentially causing the occurrence of resistance to insulin and mellitus. Diabetes may lead to dysregulation of stress hormones. Managing diabetes is essential to mitigate adverse consequences and possibly fatal complications. Medical practitioners should conduct a thorough examination of a patient's medical history to ascertain any previous instances of anxiousness since it might be a substantial root cause of diabetes. In the future, predict the risk analysis of stress and diabetes type 2 mortality rate by using multimodal algorithms.

REFERENCES

[1] Nakshine VS, Thute P, Khatib MN, Sarkar B. Increased Screen Time as a Cause of Declining Physical, Psychological Health, and Sleep Patterns: A Literary Review. Cureus. 2022 Oct 8;14(10):e30051. doi: 10.7759/cureus.30051. PMID: 36381869; PMCID: PMC9638701.

[2] https://www.diabetes.org.uk/guide-to-diabetes/emotions/stress

[3] Khalili-Mahani N, Smyrnova A, Kakinami L. To Each Stress Its Own Screen: A Cross-Sectional Survey of the Patterns of Stress and Various Screen Uses in Relation to Self-Admitted Screen Addiction. J Med Internet Res. 2019 Apr 2;21(4):e11485. doi: 10.2196/11485. PMID: 30938685; PMCID: PMC6465981.

[4] Sharma K, Akre S, Chakole S, Wanjari MB. Stress-Induced Diabetes: A Review. Cureus. 2022 Sep 13;14(9):e29142. doi: 10.7759/cureus.29142. PMID: 36258973; PMCID: PMC9561544.

[5] https://www.practo.com/healthfeed/the-dangers-of-touch-screen-phones-14729/post

[6] Li X, Zhou T, Ma H, Liang Z, Fonseca VA, et al. (2021) Replacement of sedentary behavior by various daily-life physical activities and structured exercises: genetic risk and incident type 2 diabetes. Diabetes Care 44: 2403– 2410.

[7] Goldwein O, Aframian DJ (2010) The influence of hand-held mobile phones on human parotid gland secretion. Oral Dis 16: 146–150

[8] https://www.mascoutaheyecare.com/using-your-smartphone-if-you-have-diabetic-retinopathy.

[9] Alberdi, A. Aztiria, A. BasarabTowards an automatic early stress recognition system for office environments based on multimodal measurements: a review J. Biomed. Inform., 59 (2016), pp. 49-75

[10] Karakaya M, Hacisoftaoglu RE. Comparison of smartphone-based retinal imaging systems for diabetic retinopathy detection using deep learning. BMC Bioinformatics. 2020 Jul 6;21(Suppl 4):259. doi: 10.1186/s12859-020-03587-2. PMID: 32631221; PMCID: PMC7336606.

[11] Lee, H., Choi, Y. S., Lee, S., & Park, I. P., Towards unobtrusive emotion recognition for affective social communication. In 2012 IEEE Consumer Communications and Networking Conference (CCNC), 260-264, 2012.

[12] Gao, Y., Bianchi-Berthouze, N., and Meng, H., What does touch tell us about emotions in touchscreen-based gameplay? ACM Transactions on Computer-Human Interaction (TOCHI) 19(4):31, 2012.

[13] Lau, S. H., Stress detection for keystroke dynamics. Doctoral dissertation: Carnegie Mellon University, 2018.

[14] Ghosh, S., Ganguly, N., Mitra, B., & De, P., Tapsense: Combining self-report patterns and typing characteristics for smartphone-based emotion detection. In Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services (p. 2), 2017.
[15] Cosgrove M: Do stressful life events cause type 1 diabetes? Occup Med 54. 250 –254,2004
[16] Littorin B, Sundkvist G, Nystrom L, Carlson A, Landin-Olsson M, Ostman J, Arnqvist HJ, Bjork E, Blohme G, Bolinder J, Eriksson JW, Schiersten B, Wibell L: Family characteristics and life events before the onset of autoimmune type 1 diabetes in young adults. Diabetes Care 24. 1033–1037, 2001
[17] Cox DR. The regression analysis of binary sequences. J R Stat Soc Ser B Methodol. 1958; 20(2):215–42.
[18] https://www.simplilearn.com/what-is-xgboost-algorithm-in-machine-learning-article#what_is_xgboost_algorithm.
[19] Quinlan JR. Induction of decision trees. Mach Learn. 1986; 1(1):81–106.