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Transforming Type 2 Diabetes Management through Telemedicine, Data Mining and Environmental Insights

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ABSTRACT

Diabetes mellitus is a prevalent chronic disease with significant implications for public health, counting an expanded chance of coronary heart malady, stroke, persistent kidney illness, misery, and useful inability. In India, the predominance of diabetes among grown-ups matured 20 a long time and more seasoned rose from 5.5% in 1990 to 7.7% in 2016. Traditionally, diabetes management involves costly consultations and diagnostic tests, presenting challenges for timely diagnosis and treatment. Additionally, a comprehensive study was conducted to investigate the relationship between the incidence of type 2 diabetes mellitus (T2DM) and environmental exposure to arsenic in the form of air, water, and food pathways. The majority of the analyzed studies examined the levels of arsenic in water samples, with analyses of urine, blood, serum, and plasma samples coming next. Groundwater supplies may get contaminated by arsenic, especially in regions where arsenic deposits are naturally occurring or as a result of industrial activity. Additionally, various meals contain it, particularly rice, seafood, and poultry. Besides, it might be released into the environment by industrial processes such coal combustion, smelting, and mining, which could lead to occupational exposure. There may be a genetic component to the association between arsenic exposure and the onset of diabetes. Ultimately diabetes mellitus is enhanced by arsenic pollution through air, food and drinking water. Advances in machine learning and telemedicine offer innovative solutions to address these challenges. Data mining, a crucial aspect of machine learning, facilitates the extraction of valuable insights from extensive datasets, enabling more efficient and effective diabetes management. This study explores a telemedicine-based system utilizing five classification techniques—Decision Tree, Naive Bayes, Support Vector Machine, and others—to predict Type-2 diabetes. By leveraging real-time data analysis, the system aims to enhance early diagnosis and management of Type-2 diabetes, potentially preventing progression to critical conditions. The results evaluate the effectiveness of these models in a telemedicine context, identifying the best-performing model to assist healthcare professionals in making informed decisions for early intervention and improved patient outcomes.

Key Words	Diabetes Mellitus, Type-2 Diabetes, Telemedicine, Environment, Arsenic, Machine Learning, Data Mining, Early Diagnosis, Predictive Analytics, Healthcare Management
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1. INTRODUCTION

Diabetes has developed as a worldwide wellbeing emergency, with the scourge especially articulated in South East Asia, eminently in India. Around 72 million individuals in India are evaluated to have diabetes, whereas an extra 80 million are accepted to have pre-diabetes. Type 2 diabetes accounts for over 90-95% of these cases (Desilva 2016, Gupta 2024 & Arvind 2024). Concurring to the World Wellbeing Organization (WHO), roughly 347 million individuals around the world are influenced by diabetes, and it is anticipated to gotten to be the seventh driving cause of passing all inclusive by 2030 ("WHO/diabetes" & Rahman 2023).The management of Type 2 diabetes has evolved rapidly over the past decade, with several new therapeutic agents introduced. In 2005, the Indian Council of Medical Research (ICMR) released guidelines for the management of Type 2 diabetes, which have been extensively embraced throughout the nation. A subsequent ICMR workshop in 2018 focused on refining these guidelines (Arvind 2024). The short goals of this work are to discuss certain methodological modifications related to the environment, possible fixes, and further research opportunities. At this point, the most prevalent attributes are walking distance, air pollution, food, exercise and environmental pathways (Schulz 2016).

1.1 Mechanism Linking the Environment and T2DM

Environmental, biochemical, and behavioral risk variables are thought to combine to cause type 2 diabetes (Kahn S.E 2014 & Chatterjee 2017). If there is no environment that encourages healthy lifestyles, it is taught that these lifestyles are undesirable. A comprehensive search was carried out in pubmed, scopus, web of science and embase databases. The inclusive of some criteria were studied. Diabetes is a chronic metabolic disease characterized by the body's inability to appropriately control blood sugar levels. Diabetes mellitus type 2 is a chronic metabolic disease usually shows up as adult food, and its start is caused by a complex interaction between environmental and genetic factors. This condition is characterized by insulin resistance and decreased insulin production, both of which cause long-term disruptions in glucose metabolism. As a result, high blood sugar levels can lead to a number of complications, such as cardiovascular disease, neurological conditions, kidney problems, and retinopathy. (M. Barbagallo 2022, N.R. Kakavandi 2023 & Armghan, J 2023).

Empirical data has demonstrated a probable association between diabetes and exposure to environmental arsenic. Numerous studies have shown that extended exposure to arsenic may increase the likelihood of developing diabetes. There is evidence linking the high levels of arsenic in the population's drinking water to both occupational settings and demographics (M. Halim 2019). Studies revealed a 27% increase in the risk of developing diabetes is linked to a drinking water arsenic concentration rise of 15 micrograms per liter (C. Ke, K.V 2023 & Rahmani 2023) Insulin signaling and secretion are negatively impacted by arsenic, which results in decreased glucose tolerance and elevated insulin resistance. This event raises the possibility that arsenic plays a role in the onset or exacerbation of diabetes mellitus 2. Furthermore, it has been demonstrated that exposure to arsenic increases oxidative stress and inflammation, two processes that are known to be important in the development and maintenance of diabetes (M. Nikravesh 2023, M.L. Colwell 2023 & K. Rangel-Moreno 2022).

Arsenic's effects on the advancement of diabetes have been linked in numerous research. The data points to a possible connection between inorganic arsenic and the onset of diabetes, especially in populations exposed to different concentrations of the metal. Chronic low-level arsenic exposure has been linked in certain publications to a higher prevalence of diabetes mellitus 2 (W. Li 2023, S. Shokat 2024, V.M. Nurchi 2020 & N.E. Tinkelman 2020). Polluted air can raise type 2 diabetes risk. Studies from the USA, Europe reveals that there is a definite link between incident diabetes mellitus 2 and ambient PM 2.5(fine particulate matter 2.5 micrometer diameter). In a systematic review and meta-analysis some countries showed that the risk of diabetes mellitus 2 rose by 8-10% per 10 microgram/meter increase in the exposure and the association was stronger in females. However conclusion drawn from these studies cannot be directly extra collated to developing countries.

Ambient pollution and the levels are low in high income countries. There have been a few attempts accessing the risk of diabetes associated with air pollution in developing nations where the air quality tends to be much poorer. A study from china showed a 155 increased hazards of incidents of diabetes from every 10 microgram/meter increase in fine particulate matter of diameter of less than or equal to 2.5 micrometer. Another study from china reported an increase in the fasting plasma glucose (FPG) and glycated hemoglobin (HBA1c) by 0.025 and 0.001 m mole/liter respectively for every 10 microgram/meter increase in particulate matter of diameter less than or equal to 10 micrometer and an increase by 0.061 to 0.016 m mole /liter respectively for every 10 microgram/meter increase in fine particulate matter of diameter 2.5 micrometer.

An analysis of data from nearly 4 lakhs individuals showed that exposer to the higher levels of fine particulate matter in air of diameter 2.5 micrometer was associated with not only with the increased risk of diabetes 2, but also mortality risk from base line of diabetes mellitus 2 and its complications (Mohan V 2024). In such an environment, educational and behavioral measures may be severely reduced or completely useless. Numerous studies have demonstrated the importance of behavioral, socioeconomic, demographic, and individual level factors in predicting type 2 diabetes(Gray-Webb 2013 & Agardh 2011). Reviews from the past also point to a connection between the environment and conditions like obesity, cardiovascular disease, hypertension, metabolic syndrome, and physical activity that are directly linked to type 2 diabetes (Black 2008, Sallis 2008 & Poortinga 2006).

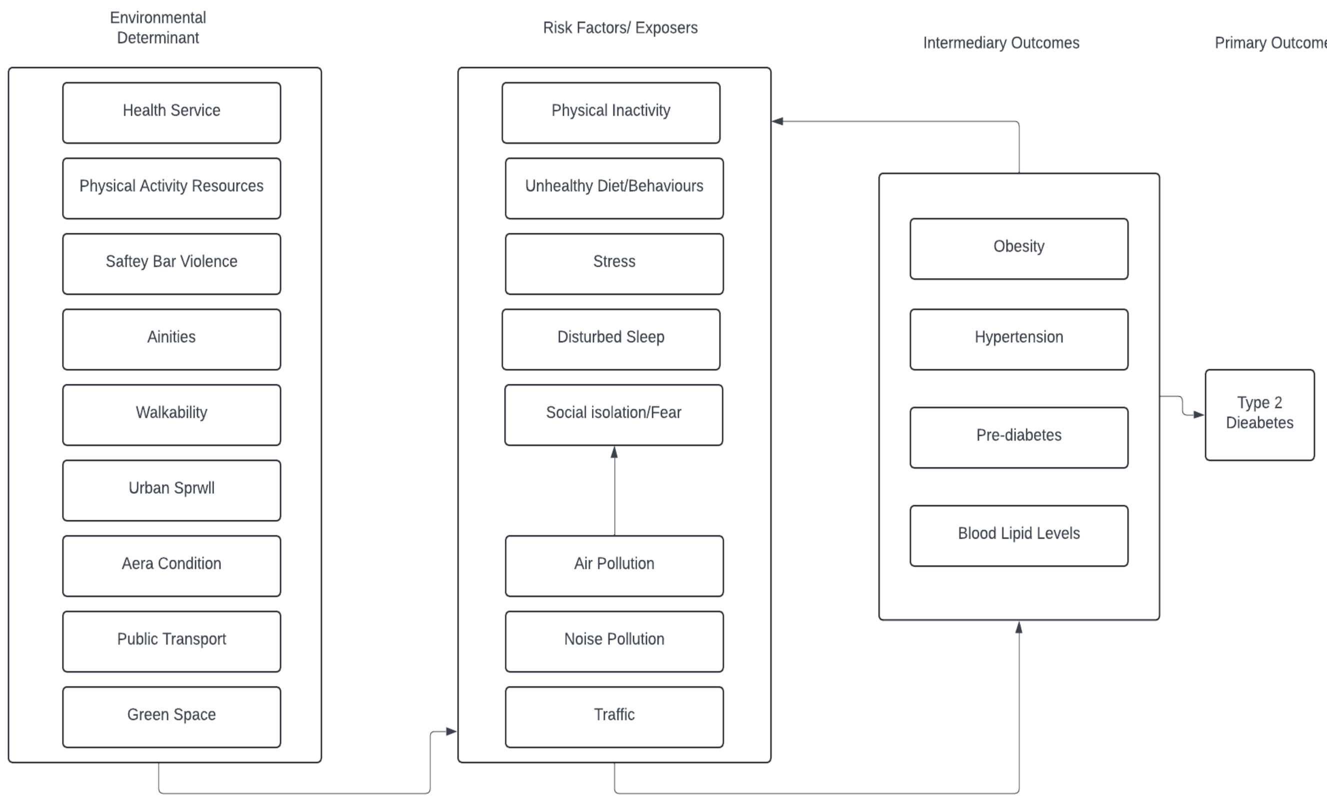

Figure 1: Diagrammatic representation of the mechanisms by which environmental factors affect the risk of Type-2 diabetes mellitus.

The hypothetical system shown in Figure 1 describes the various ways that unique environmental factors could influence type 2 diabetes. Socio-ecological theories form the basis of this paradigm; they highlight that human behavior is determined by capacity and is supported by the socio-demographic, psycho-social, economic, organizational, and physical environments (Sallis 2012). In Figure 1.1, the methods by which environmental factors affect the possibility of Type-2 diabetic complications are diagrammatically represented (Northridge 2023). Within this framework, newer advancements have led to the development of categorization models utilizing a range of machine learning approaches. By leveraging extensive or real-time data sets to aid in diagnosis and prediction, these models assist medical professionals in the identification and management of Type 2 diabetes (Arvind 2024).

1.2 Investigation

This study's main objective is to examine diabetes datasets and apply machine learning algorithms—namely Decision Tree, Random Forest, Neural Network, Support Vector Machine, and Naive Bayes—for the prediction of Type 2 diabetes (Teimoory 2024, Xiaopu 2024, Chakraborty 2023, Krishna 2024 & Uddin 2023). The research seeks to develop a robust prediction engine and a corresponding web application that enables users to predict diabetes using these algorithms. This study also explores the application of statistical models in machine learning and aims to enhance understanding of how these algorithms function in the context of diabetes prediction (Teimoory 2024 & Xiaopu 2024).

1.3 Materials and Methods

The study was done preferred reporting items for systematic reviews and meta-analysis (PRISMA) statement. Based on study criteria such as

1. Article published in English
2. Full text records
3. Articles relating arsenic exposure through the drinking water, air and food path ways and its effects on diabetes mellitus 2.
4. Exclusion criteria like books, clinical trials and conference articles.

Along with these criteria followed by real time data set and online dataset to study prevalence accessibility of diabetes mellitus 2 and its management to reduce mortality rate, it also emphasis the linkage between air pollution in the form of fine particulate matter less than or equal to 2.5 micrometer diameter and also arsenic pollution through drinking water and food and other pollutant toxin.

Diabetes mellitus is classified into the following types:

1. Type 1 Diabetes: Previously known as "Insulin-Dependent Diabetes Mellitus," this kind of the disease is caused by the body's inability to manufacture insulin (IDDM).
2. Type 2 Diabetes: This kind is marked by an absolute insulin deficit that can occasionally coexist with insulin resistance, a condition in which cells are unable to use insulin as intended. It was once referred to as "Adult-Onset Diabetes" or "Non-Insulin Dependent Diabetes Mellitus" (NIDDM).
3. Type 3 diabetes, often known as gestational diabetes, is characterized by increased blood glucose levels and affects pregnant women who have never been diagnosed with the disease (Chakraborty 2023, Krishna 2024 & Uddin 2023).
4. The following Table 1 describes Clinical Differentiation between Type 1 and Type 2 Diabetes.

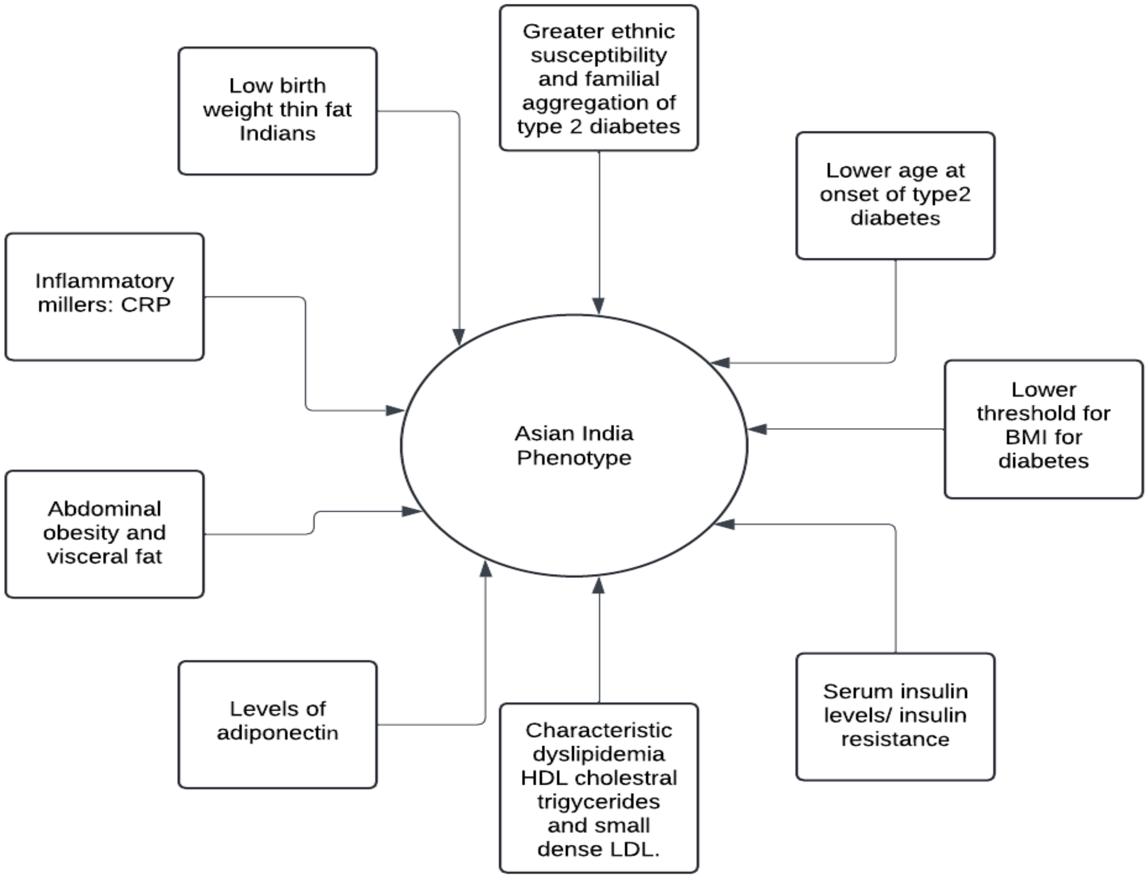

Figure 2: Block Diagram of Asian Indian Phenotype

Table 1: Clinical Differentiation between Type 1 and Type 2 Diabetes (LIANA 2024)

Clinical Point	**Type 1 Diabetes**	**Type 2 Diabetes**
Age	Typically diagnosed in youth	Commonly diagnosed in adults
Family History of Diabetes	Uncommon	Common
Ketosis at Diagnosis	Can occur	Rare
Insulin Markers	Absence	Presence
C-Peptide Assay	Lack of reserve beta cells	Presence of reserve beta cells
Pancreatic Autoantibodies	Presence	Absence

1.4 Overview of Types-2 Diabetes

Diabetes type 2 may be a complicated metabolic and vascular condition primarily marked by insulin resistance and, to differing degrees, insulin secretory absconds. It may be a dynamic condition as often as possible related with central corpulence, dyslipidemia, and hypertension. In spite of the fact that type 2 diabetes is most common among overweight and hefty people of center to late age, it is progressively watched in more youthful populaces and those with lower body mass index (BMI). Outstandingly, South Asians display the “Asian Indian phenotype,” where, at a given BMI level, Compared to Caucasians, they typically have more total body fat, extra visceral fat, increased insulin resistance, and a higher prevalence of diabetes (see Figure 2).

1.5 Data Collection

Actual data were gathered from diagnostic facilities in accordance with accepted clinical standards for the diagnosis of diabetes. The following table 2 describes diagnostic criteria for Diabetes and Pre-diabetes disease. Among the diagnostic standards used are:

- **Random Plasma Glucose**: ≥ 200 mg/dL
- **Fasting Plasma Glucose (FPG)**: ≥ 126 mg/dL
- **2-Hour Post 75g Glucose (hPG)**: ≥ 200 mg/dL
- **Glycated Hemoglobin (HbA1c)**: ≥ 6.5%

Patients presenting with symptoms such as osmotic symptoms, weight loss, tiredness, weakness, recurrent urogenital infections, and delayed wound healing were assessed. Notably, some patients with diabetes may exhibit no symptoms. Pre-diabetes, identified as impaired glucose tolerance (IGT), was also evaluated to gauge early risk.

Table 2: Diagnostic Criteria for Diabetes and Pre-diabetes

Parameter	WHO/ADA Criteria	Diabetes
Fasting Plasma Glucose (FPG) (mg/dl)	< 110 mg/dL	126 mg/dL or higher
2-Hour Postprandial Glucose(2-hPG) (mg/dl)	< 140 mg/dL	200 mg/dL or higher
Glycated Hemoglobin (HbA1c)(%)	< 5.7%	6.5% or higher
Random Plasma Glucose	Not specified	200 mg/dL or higher with symptoms

Based on family history, symptoms of insulin resistance, hypertension, dyslipidemia, and polycystic ovarian syndrome (PCOS), specialists frequently predict Type 2 diabetes. This research leverages real-time data collected at Clinical diagnostic centers to enhance prediction accuracy. Machine learning algorithms were applied to analyze patterns in the collected data. This approach aimed to improve the prediction and classification of diabetes and pre-diabetes, providing a valuable tool for doctors in the diagnostic process. The data mining techniques used were selected to identify underlying patterns and trends, thus supporting more accurate diabetes classification and management.

2. Methodology

2.1 Data Description

The evaluation of the performance of various classification algorithms on two distinct datasets and reviews relating to arsenic in drinking water, food, fine particulate matter & pollution in air to predict diabetes.

Dataset 1: the dataset is collected from online Kaggle website. It Consists of 5,000 samples with nine features including gender, age, hypertension, heart disease, smoking history, BMI, HbA1c level, blood glucose level, and diabetes as the target variable. The following Table 3 is the sample table of online dataset.

Dataset 2: the real time data set is collected from Clinical Diagnostic Center. It Comprises 48 samples with 19 features, including lab_id, gender, age, fasting blood sugar levels, postprandial blood sugar levels, HbA1c, and a target variable indicating diabetes presence. The following Table 4 is the sample table of real time dataset.

Table 3: The Sample Table of Online Dataset

SI.No	Gender	Age	hypertension	heart_ disease	smoking_ history	bmi	HbA1c_ Level	blood_ glucose_ level	diabetes
1	Female	80	0	1	never	25.19	6.6	140	0
2	Female	54	0	0	No Info	27.32	6.6	80	0
3	Male	28	0	0	never	27.32	5.7	158	0
4	Female	36	0	0	current	23.45	5	155	0
5	Male	76	1	1	current	20.14	4.8	155	0

Table 4: The Sample Table of Real Time Dataset

SI.No	lab_id	Gender	Age	fbs1	fns1	ppbs1	ppvs1	HbA1c	Mbg	result	remarks
1	4	M	49	209	1	354	1.5	9.3	220.21	1	dm
2	11	M	28	81	0	105	0	5.4	108.28	0	nd
3	12	F	25	76	0	99	0	5.1	99.67	0	nd
4	15	M	65	69	0	104	0	5.6	114.02	0	nd
5	19	M	51	164	0.5	238	1	7.3	162.81	1	dm

2.2 Data Preprocessing

Dataset 1:

- **Missing Value Imputation**: Examined for any missing data. The most frequent value was used to impute categorical data, and the mean was used for numerical features.
- **Encoding Categorical Variables**: One-hot encoding was used for categorical variables like "smoking history" and "gender," whereas label encoding was used for other variables.
- **Feature Standardization**: Standardized numerical features were given a mean of 0 and a standard deviation of 1.

Dataset 2:

- **Missing Value Handling**: Missing values were handled appropriately, with numerical features filled using the mean, and categorical features filled using the mode.
- **Feature Transformation**: Features were encoded and scaled as necessary for compatibility with the classification algorithms.

2.3 Managing Class Disparities

Dataset 1:

- Created synthetic samples for the minority class using the Synthetic Minority Over-sampling Technique (SMOTE), which balanced the distribution of classes.

Dataset 2:

- The dataset was relatively balanced, but preprocessing was applied to ensure class distributions were optimal for modeling.

2.4 Model Training and Evaluation

Dataset 1:

- Trained and evaluated six classifiers: Support Vector Machine (SVM), Decision Tree, Random Forest, Naive Bayes and Neural Network
- Split the dataset into training (70%) and testing (30%) sets.
- Employed Stratified K-Fold cross-validation (5 folds) to assess model performance.

Dataset 2:

1. Trained and evaluated the same classifiers with cross-validation techniques suited for smaller datasets.
2. Used the entire dataset for training and evaluation due to its smaller size.

2.5 Classifiers and Configurations:

- **SVM**: RBF kernel approximation.
- **Decision Tree**: Limited maximum depth to avoid overfitting.
- **Random Forest**: 100 trees with maximum depth of 10.
- **Naive Bayes**: classifier with probability based on the Bayes theorem.
- **Neural Network**: 100 neurons in a single hidden layer with ReLU activation.

3. Results and Discussions

Arsenic is a heavy metalloid that can be toxic to the body and has no place in human physiology. Type 2 diabetes is more common in people who have been exposed to high doses of arsenic over an extended period of time (C. Fan 2022, S.-M. Tsai 1999, B.Z. Guisela 2022 & M.L. Kile 2008). Due to the fact that prolonged exposure to arsenic is associated with impaired glucose tolerance and insulin resistance, two conditions that are known to exist. The characteristic insulin resistance found in people with type 2 diabetes. Uncertainty exists regarding the exact mechanisms by which arsenic influences the development of type 2 diabetes (F. Castriota 2018, Z. Ghaedrahmat 2021, B. Dalal 2010 & M.J. Spratlen 2018). The likelihood of developing diabetes increases with continuous exposure to arsenic and with increasing concentrations of the element, according to weighted data ((M.J. Spratlen 2019, X. Wang 2018 & Chang 2020). More research that looked into the quantity of arsenic in water samples was included in the review. Arsenic analysis in plasma, blood serum, and urine samples came in second. The more inferior classes included food, diet, nails, and tears in addition to air samples.

4.1 Environmental Exposure To Arsenic And Type 2 Diabetic Mellitus

Long-term exposure to arsenic through drinking water has been linked to an increased incidence of micro and Marco vascular complications of diabetes type 2—such as myocardial infractions, heart failure, stroke, retinopathy, diabetic food, and poly neuropathy (D. Jovanović 2019, L.-I. Hsu 2016, E.V. Bräuner 2014, M. Rahman 1998, A.S. Andrew 1998, A.S. Andrew & D. Chakraborti 2011). This systematic review looked at several studies that looked into the relationship between the prevalence of diabetes and long-term exposure to arsenic via food, drink, and airborne environments (D. D'Ippoliti 2010, J.-W. Huang 2014 & N.S. Rao 2022) Consuming arsenic-tainted water can lower insulin production and increase insulin resistance, which can lead to beta cell dysfunction and insulin resistance. Furthermore, oxidative stress and inflammation—both of which are connected to diabetes mellitus—can result from exposure to arsenic (37, Diaz-Villasenor 2013).

These mechanisms may explain why consuming arsenic-contaminated water results in diabetes and other associated health problems (K.A. James 2013, Fevrier-Paul 2021, Z. Drobná 2013, M. Rahman M 1999 & K. Sripaoraya 2017). Genetics and drinking water exposure to arsenic were also associated with an increased incidence of diabetes 2. People with particular mutations in the notch Recept(J.G. Spangler 2012) or 2 Gene (NOTCH2) were more likely to develop diabetes 2 when exposed to inorganic arsenic There is a correlation between the death rate from diabetes mellitus and the county-level air concentration of arsenic in each of the 100 counties of North Carolina, in addition to drinking water sources. Furthermore, it is well acknowledged that exposure to particulate matter containing arsenic, beryllium, cadmium, and nickel has a negative effect on health, potentially increasing death rates and elevating the risk of Type 2 diabetes (J.G. Spangler 2012 & E. Riseberg 2021).

4.2 Demographic Characteristics And Socio Economic Status

Based on demographic factors like gender, age, genetics, obesity, and socioeconomic level, some research demonstrates a relationship between arsenic exposure and the development of Type 2 diabetes. Regarding this, some findings were noted across a number of populations, including those in the US, Taiwan, Korea, and China. Diabetes increased the incidence of internal malignancies, such as those of the stomach, colon, liver, pancreas, and lungs. When diabetes patients had elevated arsenic levels, the correlation was especially strong (M. Hendryx 2021). For instance, the amount of 20 metals in the urine of middle-aged women participating in the study was measured. This finding indicated a link between T2DM in women and the excretion of metals like arsenic (X. Wang 2020). Thus, in order to eliminate the accessibility of heavy metals that cause T2DM and ultimately result in mortality, the primary focus needs to be on drinking water, food, and crops. In order to reduce and assist physicians in identifying the primary causes of diabetes and to identify previous treatments based on reviews and datasets that are currently available, the best machine learning techniques or classifiers were developed. This allowed medical professionals to provide direct or telemedicine care while also lowering global death rates.

3.3 Dataset Results

In Table 5,the test accuracy of five classifiers—SVM, Decision Tree, Random Forest, Naive Bayes, and Neural Network—was evaluated across two datasets is shown. On Dataset 1, Random Forest achieved the highest accuracy at 98%, followed by Neural Network (93%), Decision Tree (92%), SVM (91%), and Naive Bayes (86%). In contrast, for Dataset 2, all classifiers except the Neural Network reached 100% accuracy. The Neural Network, however, showed a significant drop to 50% accuracy on Dataset 2, suggesting potential challenges such as over fitting or data imbalance.

Table 5: Test Set Accuracy

Classifier	Dataset 1 Accuracy	Dataset 2 Accuracy
SVM	**0.91**	**1.00**
Decision Tree	**0.92**	**1.00**
Random Forest	**0.98**	**1.00**
Naive Bayes	**0.86**	**1.00**
Neural Network	**0.93**	**0.50**

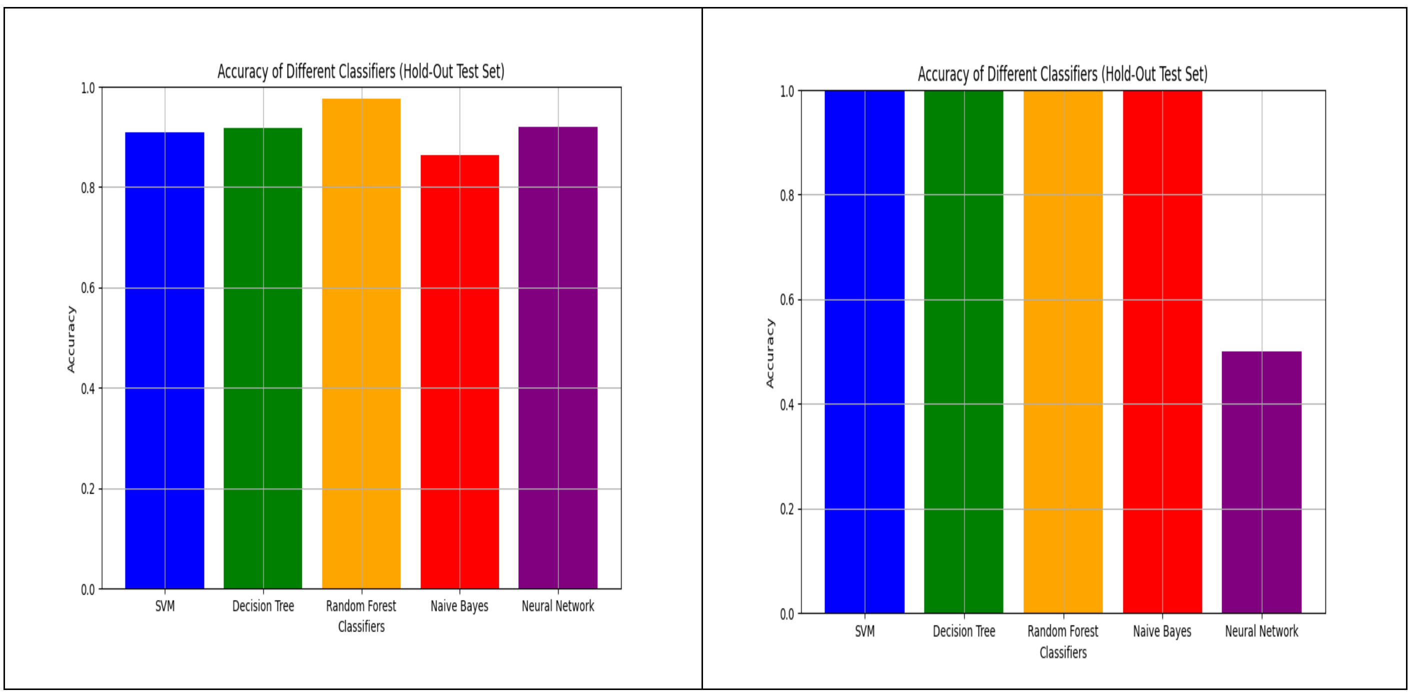

Figure 3 Accuracy of Different Classifiers on Dataset1 and Dataset2

The bar graph in Figure 3 illustrates the accuracy of five classifiers—SVM, Decision Tree, Random Forest, Naive Bayes, and Neural Network—across two datasets. Random Forest consistently achieved the highest accuracy on Dataset 1, while all classifiers except the Neural

Network reached 100% accuracy on Dataset 2. The Neural Network's significant drop in performance on Dataset 2, with only 50% accuracy, stands out, highlighting potential model-specific issues.

Table 6: Cross-Validation Accuracy

Classifier	**Dataset-1 Accuracy**	**Dataset-1 Std Dev**	**Dataset-2 Accuracy**	**Dataset-2 Std Dev**
SVM	0.91	0.01	1.00	0.00
Decision Tree	0.92	0.02	1.00	0.00
Random Forest	0.98	0.00	1.00	0.00
Naive Bayes	0.86	0.01	1.00	0.00
Neural Network	0.92	0.02	0.50	0.00

In Table 6, the cross-validation accuracy and standard deviation of five classifiers are compared across two datasets. On Dataset 1, Random Forest achieved the highest accuracy (0.98), while Naive Bayes had the lowest (0.86). For Dataset 2, all classifiers except the Neural Network achieved perfect accuracy (1.00) with no variation. The Neural Network showed a notable drop in performance on Dataset 2, with an accuracy of 0.50 and no deviation.

Table 7: Confusion Matrices

Dataset 1

SVM:

	Predicted Non-Diabetic	**Predicted Diabetic**
Actual Non-Diabetic	1357	45
Actual Diabetic	85	513

Decision Tree:

	Predicted Non-Diabetic	**Predicted Diabetic**
Actual Non-Diabetic	1360	42

Dataset 2

SVM:

	Predicted Non-Diabetic	**Predicted Diabetic**
Actual Non-Diabetic	17	0
Actual Diabetic	0	31

Decision Tree:

	Predicted Non-Diabetic	**Predicted Diabetic**
Actual Non-Diabetic	17	0

Actual Diabetic	72	526

Random Forest:

	Predicted Non-Diabetic	Predicted Diabetic
Actual Non-Diabetic	1392	10
Actual Diabetic	32	566

Naive Bayes:

	Predicted Non-Diabetic	Predicted Diabetic
Actual Non-Diabetic	1300	102
Actual Diabetic	95	503

Neural Network:

	Predicted Non-Diabetic	Predicted Diabetic
Actual Non-Diabetic	1362	40
Actual Diabetic	72	526

Actual Diabetic	0	31

Random Forest:

	Predicted Non-Diabetic	Predicted Diabetic
Actual Non-Diabetic	17	0
Actual Diabetic	0	31

Naive Bayes:

	Predicted Non-Diabetic	Predicted Diabetic
Actual Non-Diabetic	17	0
Actual Diabetic	0	31

Neural Network:

	Predicted Non-Diabetic	Predicted Diabetic
Actual Non-Diabetic	17	0
Actual Diabetic	0	31

The confusion matrices compare the performance of five classifiers—SVM, Decision Tree, Random Forest, Naive Bayes, and Neural Network—across two datasets as shown in Table 7. On Dataset 1, Random Forest exhibited the highest accuracy, with only 10 false positives and 32 false negatives, while Naive Bayes showed the most errors. For Dataset 2, all classifiers performed flawlessly, correctly classifying both non-diabetic and diabetic cases, with no misclassifications.

3.4 Key Findings

1. **Dataset Characteristics and Performance:**
   - **Dataset 1** (5,000 samples) and **Dataset 2** (48 samples) presented different challenges due to their size and feature composition. Dataset 1, with its larger size and varied features, demonstrated generally lower but still competitive accuracy scores compared to Dataset 2, which, despite its small size, showed perfect classification results for most models.

2. **Classifier Performance:**
   - **Random Forest** emerged as the most effective classifier for Dataset 1, achieving the highest cross-validation accuracy (0.98) and test set accuracy (0.98). This robustness indicates Random Forest's ability to handle complex feature interactions and its generalization capability.
   - For Dataset 2, all classifiers achieved perfect test set accuracy except neural network. However, permutation testing showed a p-value of 1.0000 for the SVM classifier, suggesting that while the model performed well, the results could be influenced by the small sample size.
3. **Model Evaluation Metrics:**
   - **Cross-Validation Accuracy**: Random Forest consistently outperformed other models in Dataset 1. For Dataset 2, classifiers achieved perfect accuracy, but this is likely influenced by the small sample size.
   - **Confusion Matrices**: The confusion matrices highlighted the models' ability to correctly classify diabetic and non-diabetic instances. For Dataset 1, Random Forest had the lowest number of misclassifications. For Dataset 2, all classifiers achieved perfect results, indicating a lack of variance in the data.
4. **Feature Importance:**
   - In Dataset 1, Random Forest's feature importance analysis identified Blood Glucose Level, HbA1c Level, and BMI as the most influential features, aligning with clinical expectations. Dataset 2's limited feature set and size did not permit a detailed feature importance analysis.

3.5 Implications

- The findings suggest that while Random Forest is a highly effective algorithm for larger, complex datasets, smaller datasets may yield inflated performance results due to limited data variability. Future research should focus on expanding dataset sizes, exploring additional features, and applying more advanced preprocessing techniques to enhance model performance and generalizability. This research work emphasis the purpose of application of data mining techniques in telemedicine.
- In the telemedicine system regular visits to the hospitals for patients suffering from diseases is minimized, since they can be expensive for rural background patients.
- During the COVID 19 pandemic the physical presence of the patients and doctors became risky. People preferred Telemedicine system.
- Telemedicine services done through video conferences & smart phone which reduce the time and cost to patients.
- Furthermore telemedicine system has a fast and advantageous characteristics. It can stream line the work flow of the hospitals and clinics.
- This method is more useful in natural calamities , floods , at the war zones and rural areas all over the world.
- The telemedicine system would make easier to monitor ,discharged patients and manage their recovery from disease and reduce mortality rates.

4. Conclusion

This systematic review and dataset study discusses the relationship between type 2 diabetes and arsenic exposure. Research has indicated that extended exposure to arsenic by ingestion or work-related exposure heightens the likelihood of acquiring Type 2 diabetes. Insulin resistance is thought to be caused by exposure to arsenic, which is thought to alter how the body uses insulin and how it is released. It is linked to inflammation and stress as well. The information now available suggests a possible link between TF2DM and environmental arsenic exposure from food, water, and the air. The review reveals a close connection between T2DM and environmental degradation. This study presents a straightforward approach for assessing the prevalence of type 2 diabetes through dataset analysis utilizing different classifiers. It finds that the Random Forest classifier consistently delivers superior performance, achieving perfect accuracy of 100% on both real-time datasets. The research compares various classifiers, including SVM, Random Forest, Naive Bayes, Neural Network, and Decision Tree, ultimately identifying Random Forest as the most effective method for disease prediction in telemedicine. With accuracy rates of 98% and 100% for online datasets, Random Forest is highlighted as the best option for detecting, controlling, and monitoring prevalent diseases while helping to reduce mortality rates. Thus, data mining techniques emerge as powerful tools for predicting and monitoring diseases within telemedicine systems. Doctors can use these accurate classifiers to help patients lead healthy lives, control the mortality rates in remote areas using telemedicine systems, or use a personal approach. In order to stop the disease's escalating burden, a fuller understanding of the connection between the environment and type 2 diabetes can assist develop health-promoting policies and offer opportunities for people to translate their intentions into long-lasting behavioral adjustments.

5. Future Work

Further investigations are needed to:

- **Expand Dataset Size**: Get more samples to make sure the models are reliable and applicable to a wider range of situations.
- **Explore Additional Features**: Integrate more relevant features that could enhance predictive performance.
- **Hyper-parameter Tuning**: Perform extensive hyper-parameter optimization to further improve model accuracy.
- **Advanced Techniques**: Implement ensemble methods and deep learning approaches to address limitations observed in smaller datasets.

For future research, several key areas warrant attention: First, expanding the dataset size is crucial to obtain a more comprehensive range of samples, which will enhance the reliability and generalizability of the models across diverse situations. Second, exploring additional relevant features may significantly improve predictive performance, as incorporating more data points can provide a richer context for classification. Third, hyper parameter tuning should be prioritized to optimize model accuracy, allowing for fine-tuning of the algorithms to achieve better results. Finally, implementing advanced techniques, such as ensemble methods or deep learning approaches, can help overcome the limitations associated with smaller datasets and improve predictive capabilities in the context of telemedicine. This study underscores the importance of selecting appropriate models and evaluation techniques based on dataset characteristics and highlight the need for careful consideration of model performance metrics, especially in cases with small sample sizes.

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8. International Journal for Research in Applied Science & Engineering Technology (IJRASET) ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 12 Issue V May 2024- Available at www.ijraset.com ©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 | 3360 Dialearner: Predicting Diabetes with Machine Learning Pranjal Jagtap1 , Vaishnavi Kad2 , Pratiksha Nimbalkar3 , Yashshree Shah4 , Arunadevi Khaple5 Department of Computer Engineering, Zeal College of Engineering and Research, Pune, Maharashtra. https://www.ijraset.com/best-journal/dialearner-predicting-diabetes-with-machine-learning
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