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*RESEARCH ARTICLE*

# ASSESSMENT AND EVALUATION OF LIFESTYLE FACTORS IMPACTING GLYCEMIC CONTROL

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*Abstract*

Glycemic Control is a major determinant for people with prediabetes and diabetes. Lifestyle factors plays major role in diabetes.It influence and affect the regulation of blood sugar levels.Adopting a balanced lifestyle is a critical determinant of both physical health and economic well-being.Poor health often reflects an individual's sedentary lifestyle.Every individual should prioritize their health. An unhealthy lifestyle is a gateway to diseases. These diseases can only be managed and controlled but cannot be cured. Diabetes is a progressive condition that tends to worsen over time, leading to increased complications. Technology advances are a blessing to mankind for managing the health in a proper way. Machinelearning, which is a subset of Artificial Intelligence is aiding medical field to identify the crucial features that are very relevant to diseases. In this paper the lifestyle features are identified that results in the major complications in diabetic population.



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## Introduction:-

Lifestyle is the way a person lives. It includes the activities from morning to night. Start from morning eating habits to night sleep patterns. Individual health will get affected if they have sedentary lifestyle. The diseases which we get depending upon our lifestyle are called chronic diseases. These diseases cannot be cured but can be managed and controlled effectively. There are many chronic diseases like lung cancer, diabetes, stroke, and various cardiovascular problems. Diabetes is a chronic disease that is affecting millions of people all over the world. It is growing exponentially and is affecting every age group. Diabetes is a chronic condition that affects body glucose levels. It is of two types: Type 1 and Type 2. Type 1 is insulin dependent and normally diagnosed in childhood. It affects autoimmune cells that produce insulin. Type 2 is insulin independent and often associated with life modifiable factors and can be effectively managed with a change in lifestyle choices. Type 2 diabetes is also called diabetes mellitus. If not properly managed, diabetes can lead to various health complications, as it impacts nearly every part of the body. After its diagnosis there is a need to take extra care of the individual lifestyle habits as it will further result in health complications. Its complications can be defeated with the right care and knowledge. Effective diabetes management requires developing a structured approach to improve the condition and prevent complications. These complications cannot be predicted. Key reason for the deterioration of the diabetic complications is lifestyle. There is a need to check various parameters of a diabetic individual. The very first and foremost parameter is to manage ABCs(A1C,blood pressure, cholesterol) by regular monitoring ,taking medications and maintaining proper weight with healthy diet. The progression of the disease will further lead to health deterioration which will cost both money and life. The individual can also be physically challenged or can have other health issues that result in bad health conditions. It is considered as the major reason of mortality and morbidity all over the world. There is a dire need to find and identify the key parameters in the lifestyle that cause

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and sources the disease. Feature selection and identification will help us to understand the relationship between progressions of the disease. Feature selection in machine learning work toward identifying a subset of relevant features. It focused on identifying significant features depending upon the numeric values within an interval range. It evaluates and assesses the crucial parameters of disease that are essential to be studied. Identification of patterns and lifestyle that influence blood glucose levels using machine learning. The progression of the disease can be measured by keeping track of lifestyle that elevates the glucose levels. Progression of disease from mild to moderate, severe, and critical condition can be identified only by patterns that can be taken from medical records, symptoms, and genes. The focus of the research is to identify patterns of patients' clinical profile with diseases by selecting key parameters of the disease complications. Analysis from data can be done by finding the variance between normal and abnormal values for specified diabetic complications. Silent progression and less awareness will increase the diabetic complications

## Literature Review:-

Previous research has predominantly focused on individual lifestyle factors such as diet or physical activity concerning glycemic control, overlooking the collective influence of various lifestyle factors on diabetes management outcomes. For instance, while dietary habits have been extensively studied (Evert et al., 2019), the comprehensive evaluation of lifestyle factors, including diet, physical activity, sleep patterns, psychosocial factors, and medication adherence, remains limited. Therefore, this study aims to bridge this gap by comprehensively examining the interplay between these factors and their combined impact on glycemic control and health outcomes in diabetic individuals. Many studies have been conducted in relatively homogeneous populations, neglecting the influence of cultural, socioeconomic, and demographic factors on diabetes outcomes. For instance, Morrato et al. (2017) highlighted the need for research that considers diverse populations. Therefore, this study endeavors to fill this gap by including participants from diverse demographic backgrounds, enabling a more nuanced understanding of how lifestyle factors affect glycemic control and health outcomes across different populations. Longitudinal While short-term effects of lifestyle interventions on glycemic control have been investigated, there is a dearth of research examining their long-term sustainability and effectiveness. For example, Shrivastava et al. (2020) emphasized the importance of longitudinal studies. Thus, this study seeks to address this gap by implementing a longitudinal study design, allowing for the assessment of how lifestyle changes impact glycemic control and health outcomes over time. Previous research has heavily relied on self-reported data, which may be subject to recall bias and inaccuracies. Despite this, objective measures such as biochemical analyses and objective assessments of physical activity and sleep patterns have been underutilized. As highlighted by Liu et al. (2015), this integration is crucial for a robust evaluation of lifestyle factors and their impact on diabetes outcomes. Therefore, this study aims to overcome this limitation by integrating objective measures with self-reported data, providing a more comprehensive evaluation of lifestyle factors and their influence on diabetes management outcomes.

**Dataset**

The Diabetes health indicators dataset available on kaggle has 21 features variables. This dataset can be used for the classification of prediabetes, normal and diabetes on the basis of 21 lifestyle attributes .These attributes provides a range of information like highBP, high Cholesterol, smoking, eating fruits and vegetables and so on. This dataset provides valuable insights of lifestyle parameters and health indicators that can be used as the basis of diabetes stage classification.

| | | | |
|---|---|---|---|
| 1 | HighBP | 12 | AnyHealthcare |
| 2 | HighChol | 13 | NoDocbcCost |
| 3 | CholCheck | 14 | GenHlth |
| 4 | BMI | 15 | MentHlth |
| 5 | Smoker | 16 | PhysHlth |
| 6 | Stroke | 17 | DiffWalk |
| 7 | HeartDiseaseorAttack | 18 | Sex |
| 8 | PhysActivity | 19 | Age |
| 9 | Fruits | 20 | Education |
| 10 | Veggies | 21 | Income |
| 11 | HvyAlcoholConsump | | |

**Exploratory Data Analysis**

The diabetes health indicators datasets shows a valuable insights from our daily lifestyle that indicates towards the disease stage like normal, prediabetes or diabetes

The importance of various health indicators from the dataset are shown with the help of feature importance as shown in figure.

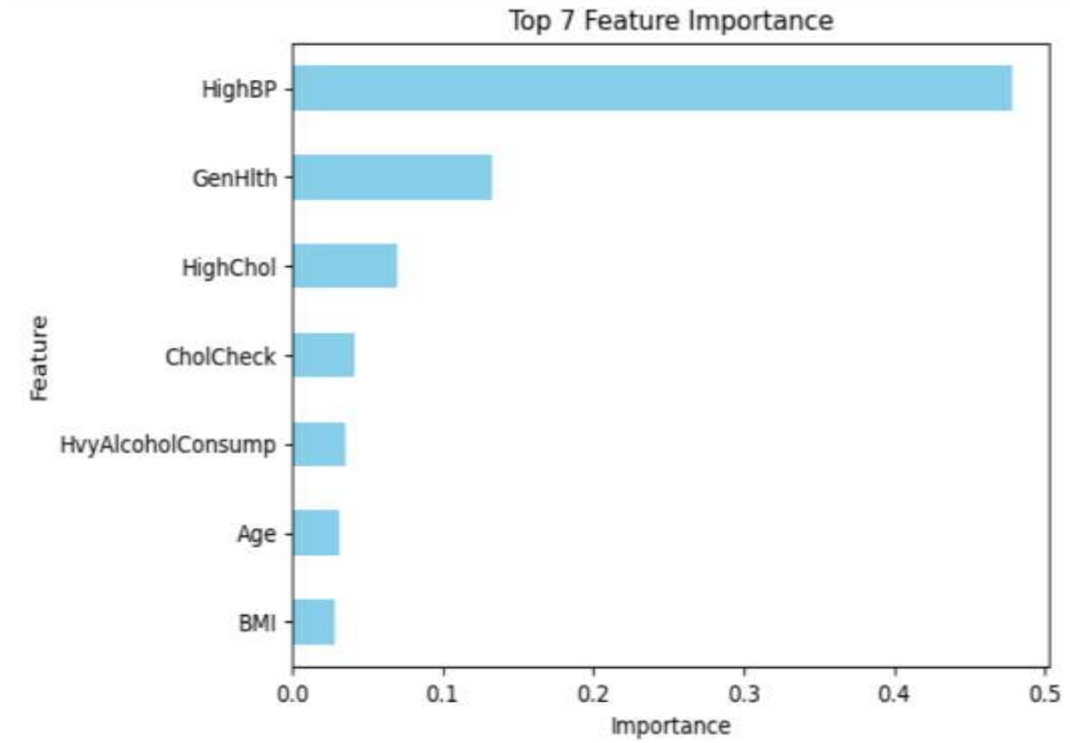


**Figure 1:-** Feature Importance.

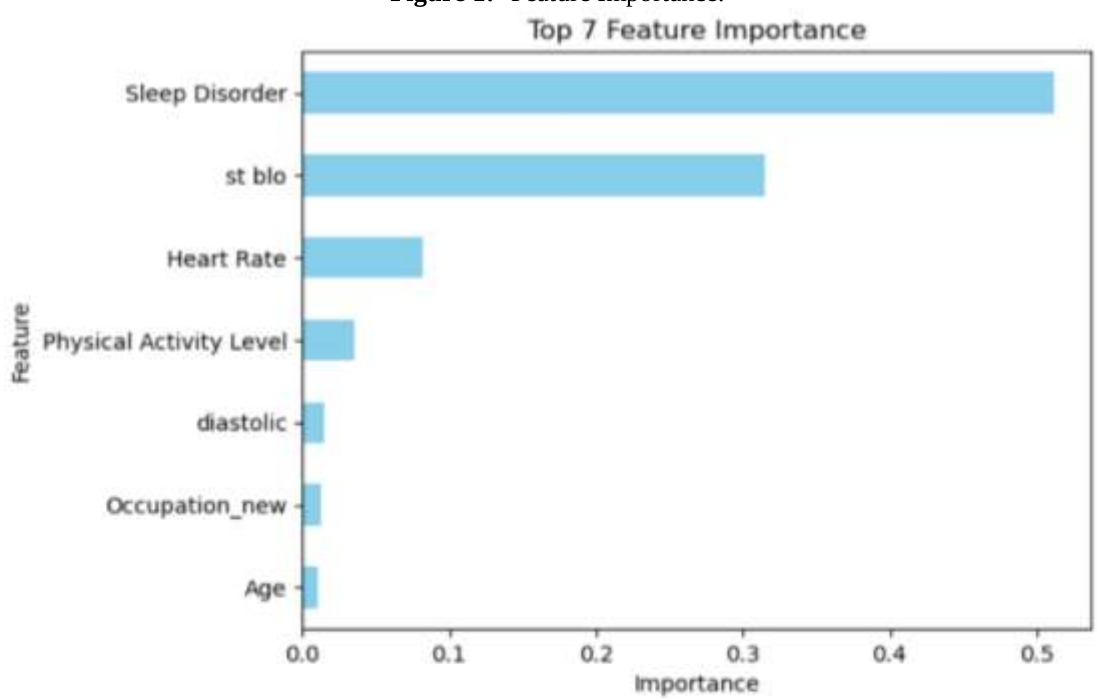


**Fig2. Sleep and lifestyle**

Out of 21 features from lifestyle these are the seven major determinants that need to be monitored for the classification of disease that affects the glycemic control. The prediabetes stage can be cured if it is diagnosed at an early stage. The lifestyle needs to be managed with controlling all the above features so that we can lead a healthy life. Every Body has a different body composition but these parameters are highly associated with glycemic control. There is a need to modify the lifestyle which will help to control the disease rather to progress towards disease complications. As the technology is impacting everybody's life from child to elderly people. Sleep patterns and mental health, occupation are also considered, as the key factors for glycemic control which are not present in thisdataset. These factors are stored in a separate dataset called sleep and lifestyle present on the kaggle.

Evaluation and Assessment of lifestyle factors are crucial for glycemic control. Early Identification can prevent or delay the progression of the disease. Addressing lifestyle factors acknowledges the complex interplay of behavioural, physiological, and psychosocial elements, to empower patients in self-management.

Methodology for Lifestyle Assessment impacting glycemic control

- **Dietary Analysis**: Use of food diaries, 24-hour dietary recalls, and validated questionnaires to evaluate dietary intake and patterns.
- **Physical Activity Monitoring**: Wearable devices, accelerometers, and self-reported activity logs to measure exercise levels and sedentary behavior.
- **Sleep Assessment**: Polysomnography, actigraphy, and sleep questionnaires to assess sleep duration and quality.
- **Stress Evaluation**: Standardized scales, such as the Perceived Stress Scale (PSS) and Beck Depression Inventory (BDI), to gauge psychological stress and mental health status.
- **Substance Use Assessment**: Surveys and biomarkers to evaluate alcohol consumption and smoking habits.

## Conclusion:-

Lifestyle factors, including diet, physical activity, sleep, stress, alcohol, and tobacco use, significantly influence glycemic control. Comprehensive assessment and personalized interventions are essential to optimize blood glucose levels and prevent diabetes-related complications. Future research should focus on integrating emerging technologies, addressing socioeconomic disparities, and exploring novel intervention strategies to enhance glycemic management. A combined dataset incorporating lifestyle factors, clinical outcomes, and behavioural patterns would facilitate more robust analyses and personalized intervention designs. This dataset should integrate data from diverse populations to ensure inclusivity and generalizability. Additionally, leveraging machine learning and predictive modelling can uncover hidden patterns and identify high-impact lifestyle modifications tailored to individual needs.

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