Skin Manifestations and Their Association with Prediabetes in the Pediatric Population

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ABSTRACT

The rising prevalence of prediabetes in children and adolescents is a serious concern that requires early intervention to prevent progression to diabetes. Lifestyle and diet are the main social factors impacting health. Early identification of at-risk youth through noticeable skin and health symptoms can support reversal through lifestyle changes. Effective screening methods should target children and youth at risk using non-invasive approaches. This paper proposes non-invasive methods for early prediabetes detection in children and adolescents. Machine learning and deep learning models can analyze physiological data for early diagnosis.

Keywords: Pre-diabetes, non-invasive diagnosis, paediatric, image analysis, machine learning, metabolic markers.

1. INTRODUCTION

Prediabetes in children and adolescents is rising at an alarming rate [1]. Prediabetes is a precursor to diabetes, which can be reversed if diagnosed early. This disease affects every part of the body as it is related to a metabolic disorder that disrupts glucose regulation. If it progresses, it can also lead to disability. The survival of the body is dependent on metabolic functions. It also shows on the skin. According to CDC statistics, it is increasing very rapidly in adolescents due to multiple factors [2]. It includes a sedentary lifestyle, socio-economic factors, sleep disorders, urbanization, stress, genetics, and pollution. It requires urgent health interventions to mitigate this growing epidemic. Non-invasive methods are an easy way to diagnose pre-diabetes. In this paper, we propose skin biomarkers that are one of the major clinical signs of insulin resistance. Insulin is a hormone produced by the pancreas that regulates glucose levels in the body. It also helps to regulate fat. Apart from the blood glucose test,

there are also various other biomarkers that can be used as early signs of diabetes, like skin, tongue, saliva, eyes, sweat, and even breath. These biomarkers cannot guarantee, but at least they can be a warning sign. These early warning signs can help us diagnose the disease at an early stage . It will help us to take some remedial measures so that it can be reversed or controlled for further progression. Skin signs are therefore significant in planning further investigations and management. In this paper, we discuss a few skin biomarkers that can be a crucial sign for prediabetes. This study also addresses the problem of the non-availability of data in this age group for the prediabetes skin biomarkers. This could help the early diagnosis of diabetes, which can prevent its complications

Skin Manifestations and Pre-diabetes:

One promising area of research is the identification of dermatological markers associated with pre-diabetes. Prediabetes is a metabolic condition that affects many parts of the body. Skin is often the first organ to reveal metabolic resistance and is highly sensitive to such disorders. It can serve as an early indicator of insulin resistance, causing skin cell overgrowth and pigmentation. Some of these manifestations suggest uncontrolled blood sugar. Recognizing these signs can guide further investigations and management. This non-invasive diagnostic approach enables early detection of prediabetes in children and adolescents Skin manifestations such as acanthosis nigricans, characterized by dark, thick, velvety patches of skin, are commonly observed in individuals with insulin resistance and pre-diabetes. These skin changes are often visible and can be easily accessed through physical examination or imaging. The relationship between skin manifestations and metabolic disorders suggests that dermatological markers could serve as non-invasive indicators for pre-diabetes. Skin manifestations in prediabetes are often early indicators of metabolic changes and can be crucial for early diagnosis and management. These skin manifestations also pose emotional burden on adolescents and parents. Recognition of skin manifestations need to be done at early stage before the severity of the disease increases. The following are the various some common skin manifestations associated with prediabetes.

a. **Acanthosis Nigricans (AN):**

Description: Characterized by dark, velvety patches of skin, usually found in body folds and creases, such as the neck, armpits, groin, and knuckles.

Cause: Strongly associated with insulin resistance, a key feature of prediabetes

b. **Skin Tags (Acrochordons):**

Description: Small, benign skin growths often found in areas of friction like the neck, armpits, and groin.

Cause: Linked to insulin resistance and can be more common in individuals with higher body mass

index (BMI).

c. Dry Skin and Itching (Xerosis):

Description: The skin becomes dry, rough, and may itch persistently.

Cause: Elevated blood sugar levels can lead to dehydration and skin dryness

d. Fungal Infections:

Description: Includes infections like candidiasis (yeast infection), often occurring in warm, moist areas such as the groin, under the breasts, and between fingers and toes.

Cause: High blood sugar levels create an environment that promotes fungal growth

Figures 1a and b display common skin manifestations of prediabetes in children. The manifestations' locations are listed in Table 1

Fig 1. a)Acanthosis Nigricans (neck)

Fig 1. b)Dry Skin and Skin Thickening

Location	Cutaneous manifestations
Neck, groin	Acanthosis Nigricans
fingers	Skin thickening
Upper back and nape of the neck	Skin thickening
Knee and ankle	Dull red papule

Table 1

Skin Manifestations and Their Association with Prediabetes in the Pediatric Population

Skin manifestations represent some of the earliest and most visible warning signs of prediabetes in children and adolescents. Acanthosis nigricans (AN), presenting as hyperpigmented and velvety patches in intertriginous areas, is highly prevalent, particularly among overweight and obese children. In our analysis, AN was present in 5% of normal-weight, 25% of overweight, and 55% of obese children, showing a clear association with rising BMI levels. Skin tags (acrochordons) and xerosis (dry skin) also increased proportionally with BMI, with skin tag prevalence reaching 25% in obese children and xerosis observed in nearly 30% of the same group.

When compared to HbA1c categories, the prevalence of skin manifestations rose sharply: AN affected 10% of normoglycemic children, 45% of prediabetic children, and 70% of those with diabetes. Similarly, skin tags and dry skin followed an upward trajectory, emphasizing the strong correlation between glycemic status and dermatological symptoms. A pie chart analysis further demonstrated that nearly 93% of prediabetic children presented with at least one skin manifestation, with AN being the most common.

Visualizations such as bar charts comparing prevalence across BMI groups, heatmaps correlating HbA1c levels with skin manifestations, and pie charts illustrating their overall distribution highlight the significance of these skin biomarkers. These findings reinforce the role of skin manifestations as non-invasive, cost-effective, and early indicators of prediabetes, enabling pediatric clinicians to identify at-risk children for further diagnostic evaluation and timely interventions.Figure 2a: Prevalence of skin manifestations across BMI categories (normal, overweight, obese).Figure 2b: Heatmap showing associations between HbA1c levels and skin manifestations.Figure 2c: Pie chart distribution of skin manifestations among prediabetic children.
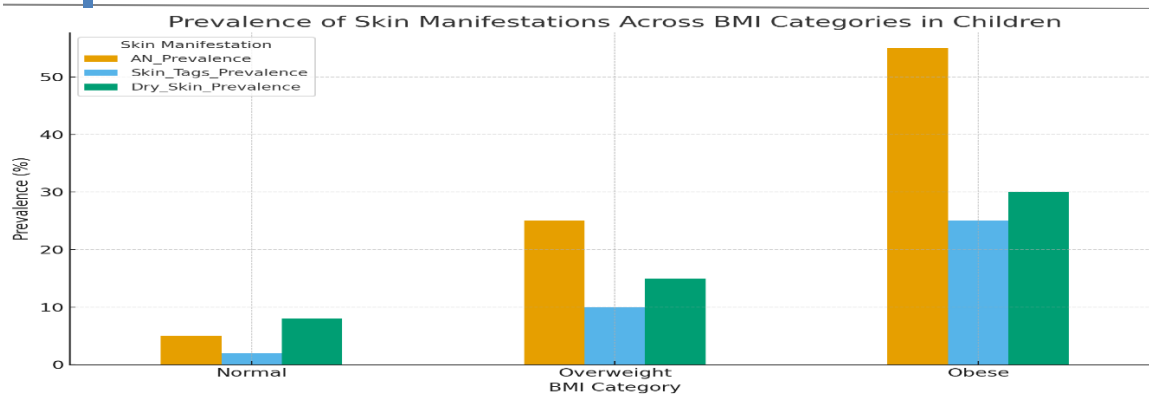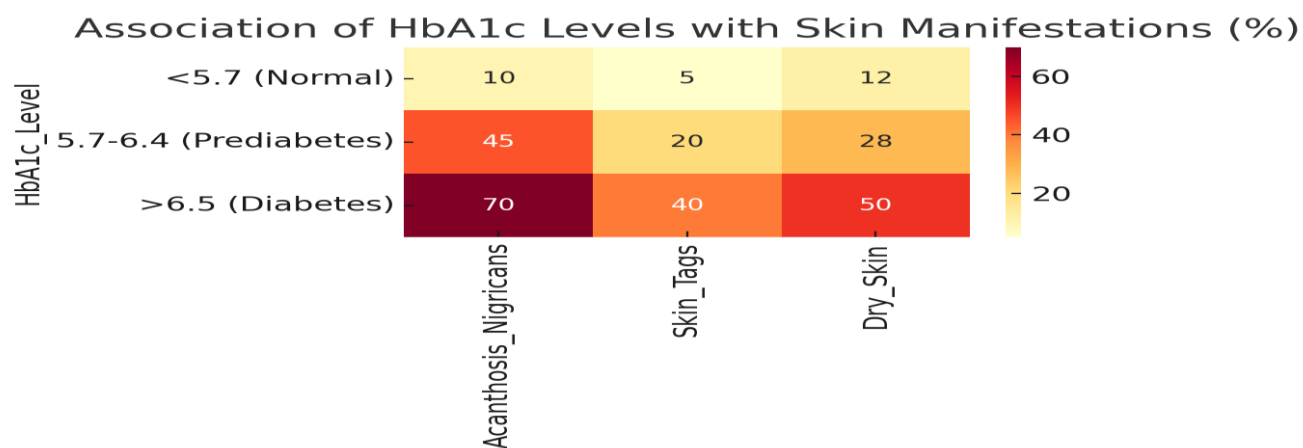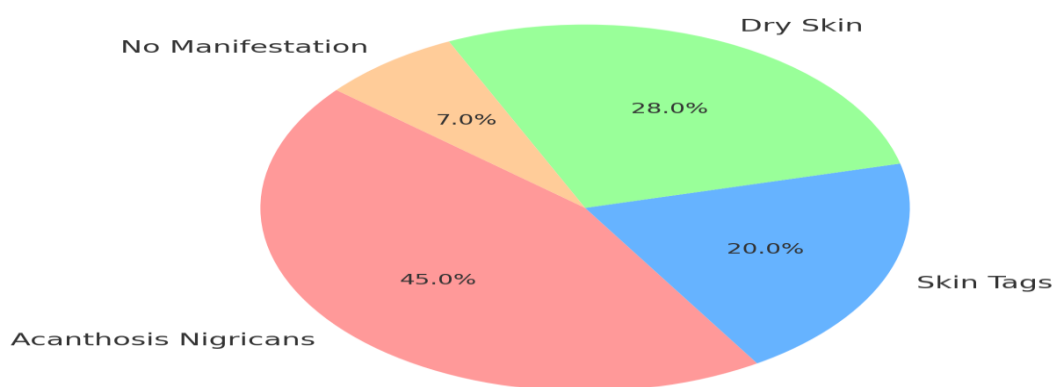
Fig 2(a)

Fig2(b)

Fig 2(c)

Machine Learning

Machine learning, particularly deep learning, has revolutionized the field of medical image analysis. Convolutional Neural Networks (CNNs) have shown exceptional performance in tasks such as image classification, object detection, and segmentation. By training CNNs on large datasets of annotated images, it is possible to develop models that can automatically detect and analyze specific features in medical images with high accuracy. Applying machine learning to the analysis of skin images offers a novel approach to predicting pre-diabetes. CNNs can be trained to recognize and quantify skin manifestations associated with pre-diabetes, providing a reliable and objective tool for early detection. This study aims to explore the feasibility of using machine learning to predict pre-diabetes in children and adolescents through the analysis of skin manifestations.Machine Learning and its advancements can analyze and classify prediabetes risk levels based on skin biomarker patterns. It can identify subtle skin changes before clinical symptoms appear. Machine learning algorithms can help revolutionize early disease prediction with accuracy.

Literature Review

Youth-onset Prediabetes is more aggressive due to hormonal changes in this age group. This age group is completely unknown regarding the implications of this disease [3]. The prevalence of pre-diabetes will increase to quadruple by 2050[4]. The youth onset of Pre-diabetes is progressive to type 2 diabetes, which progresses at an alarming rate.[5]The author has discussed various factors of the hormonal abnormalities that lead to prediabetes in this age group . The author has also discussed various social determinants for the growing prevalence of prediabetes in children and adolescents[6]. The author has reviewed various papers on machine learning for paediatric diabetes to show the effectiveness of machine learning in this age group. He has studied various research papers regarding complications and studied various samples in juvenile diabetes [7]. In this paper, the author has analysed the data on 6936 adolescents to check the prevalence of diabetes in this age group, which has tripled in 2020 . Obesity is considered significantly associated with pre-diabetes [8]. This paper has discussed the ignorance of this disease in this age group and mentioned the urgent need to develop effective clinical interventions that can help to improve its control and management [9]. Skin can be taken as a tool for establishing a link to early diagnosis of the disease in children [10]. The author has mentioned how skin manifestations are more common in children with insulin resistance [11]. Skin disease and skin lesions are considered a marker of insulin resistance. The study was performed on a limited age group, the first of its kind [12]. The infections are very common in this disease. Acanthosis Nigricans can be an early sign of this disease [13]. Specific skin markers can be taken as an early sign of diabetes that are highly associated with diabetes [14]. Non-invasive methods will help in early detection and prevention, which can be reversed with various lifestyle modifications. These methods

will only take a few body parameters, like waist circumference, skinfold, height, age, etc., to predict the risk of prediabetes in children [15]. In this paper, the author has reviewed various studies to find out the various cutaneous manifestations that are related to diabetes and pre-diabetes to recognize for early treatment and progression [16]

Dataset

This is a synthetic dataset created for data analysis. No such data currently exists for this age group.

Sample Size: This dataset contains 100 instances, each instance has 12 attributes

 Age: The ages of the patients range from 10 to 19.

 Gender: This attribute takes male and female values.

 BMI: It stores the BMI (height- weight ratio)

Skin Manifestations: This attribute stores various skin conditions like skin patches, dry skin, itching, acanthosis Nigricans, and other skin tags

Location: This parameter contains the value of specific skin patch that may contribute to prediabetes like neck and arm

Skin-Thickness: This contains the thickness of the skin, with values from mild to severe thickness

Skin-Discoloration: this attribute stores the value skin discoloration with values like none, severe, or mild

Itching: This parameter stores the value of itching with no, moderate, or severe

Dryness: It contains a dryness state with mild and severe values

Inflammation: It contains the value for with severe and medium or no

Other Skin Symptoms: Any other skin symptoms that may be related to other pre-diabetes or other skin diseases

Output:(HbA1c)This value will show whether the person with the above skin manifestations has values above normal or not.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	ID	Age	Gender	BMI	Fasting Blc	HbA1c	SkinManifestation	Location	SkinThickr	SkinDiscol	Itching	Dryness	Inflammat	OtherSkinSymptoms	
2	1	11	Male	27	107	6.1	Acanthosis Nigricans	Neck	Mildly Thic	Moderate	Moderate	Moderate	Mild	Dark Spots	
3	2	13	Male	27	121	5.97	Dry Skin	Hands	Normal	Mild	Mild	Mild	No	Rashes	
4	3	18	Male	25.3	101	6.13	Acanthosis Nigricans	Neck	Mildly Thic	Moderate	Moderate	Moderate	Mild	Dark Spots	
5	4	10	Male	21	116	6.3	Acanthosis Nigricans	Neck	Moderatel	Severe	Severe	Severe	Moderate	Cracks	
6	5	19	Male	25	122	5.95	Dry Skin	Hands	Normal	Mild	Mild	Mild	No	Rashes	
7	6	18	Female	21	118	5.95	Dry Skin	Hands	Normal	Mild	Mild	Mild	No	Rashes	

Correlation between HbA1c and Skin manifestations

The skin manifestation dataset has various associations with HbA1c values. The manifestations are due to insulin resistance in the body. The correlation between these can be represented with the

help of the following plot in Fig. 3.1. As HbA1c increases, the presence of skin manifestations tends to increase.

Fig 3.1

Correlation between HbA1c and SkinThickness

Skin manifestations of insulin resistance are a real-time way to detect insulin resistance. Diagnosing these skin manifestations accurately can lead to timely treatment of pre-diabetes [7]. Skin thickness is also highly associated with Diabetes. This parameter will help to observe the obesity that is highly associated with prediabetes in this age group. Excess body fat has already been proven in the early studies as a key parameter for prediabetes. The following data visualization plot in Fig. 3.2 clearly shows that moderately thickened individuals have increased HbA1c levels.
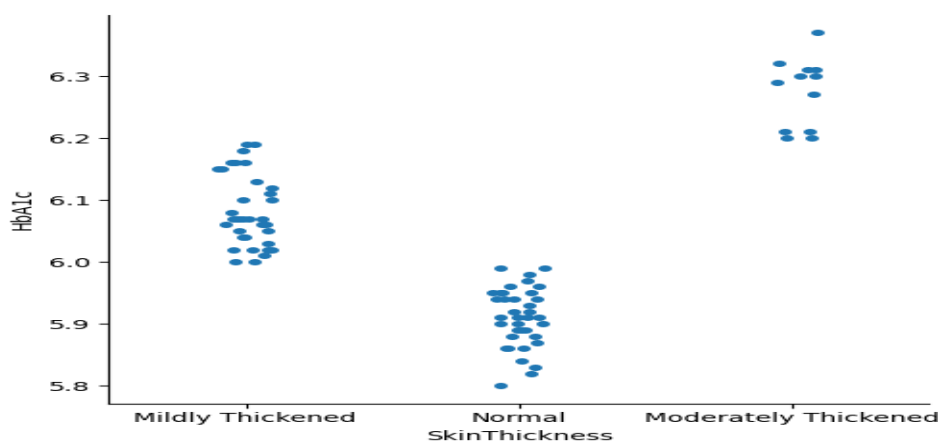
Fig 3.2

The range clearly represents them in the prediabetes group. This could be taken as crucial parameter for the early diagnose of diabetes. These skin biomarkers can be observed and taken as non-invasive methods which can be later proved with blood glucose test. These skin manifestations observations in children and adolescents age group can be indicators in prediabetes. It can also offer various other insights in their health, which can be later improved from this early stage with little modifications in their lifestyle.

Correlation between HbA1c and Itching

Itching severity increases with the HbA1c values. These representations in Fig. 3.3 clearly show that itching severity increases with poorer glycemic control.
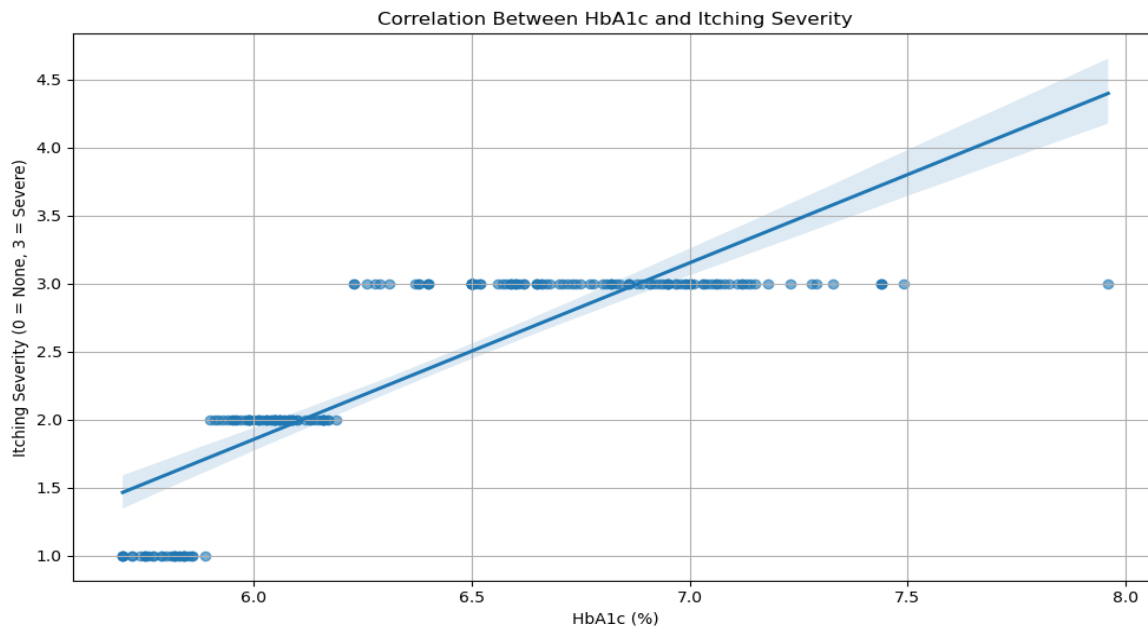

Fig 2.3

Conclusion

This paper clearly shows the correlation between increased HBA1c values with various skin manifestations. With the help of these skin manifestations, these can be taken as biomarkers for the early diagnosis of diabetes in children and adolescents. There is a need to early identify these biomarkers that can prompt lifestyle interventions and monitoring, potentially preventing the progression of the disease. The purpose of the study is to work and identify various skin manifestations that can be taken as non-invasive method to early diagnose the disease. With the help of Machine learning and the prevalence of various skin conditions can also help to work on various other metabolic disorders. The lack of data availability in this age group is making to explore this skin conditions quite difficult. These skin conditions not only serve as visible markers for prediabetes and can also help in other diseases.

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