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Narrative Review

Studies on Artificial Intelligence (AI) Techniques for Diabetes Diagnosis Using Facial Features

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Abstract
Diabetes Mellitus (DM) stands as one of the most widespread non-infectious diseases globally. Although diagnosis of diabetes is possible with the fasting plasma glucose test after 12-hour fast, once diabetes is diagnosed, it cannot be reversed. Therefore, it is crucial to identify early indicators for predicting diabetes.

Presently, DM can be discerned through various methods involving the analysis of human facial features. One method for facial recognition in diabetes relies on experimental evidence, with its accuracy contingent on the skill and expertise of the physician.

Another approach involves diagnosis based on facial morphological features. These morphological changes may be attributed to oxidative stress, damage of blood vessels and collagen, edema and craniofacial abnormalities stemming from hyperglycemia. While cephalometric analysis remains the gold standard for diagnosing skeletal craniofacial morphology, it is a costly and technique-sensitive procedure.

Facial recognition based on Artificial Intelligence (AI) has proven to be a valuable tool in the diagnosis and screening of diabetes. Its combination of simplicity, accuracy, and cost-effectiveness makes it a promising addition to the healthcare landscape, ultimately contributing to advancements in pre-clinical diagnosis and leading to enhanced patient outcomes.

Given the rapid global increase in diabetes, the importance of early detection of diabetes and the limited information about the role of facial recognition in this regard, this study assesses diabetes through facial features using AI approaches.

Keywords: Artificial intelligence, Diabetes mellitus, Facial recognition, Oxidative Stress

Introduction

The most prevalent non-infectious disease in the world is Diabetes Mellitus (DM) (1-8). According to the World Health Organization, 171 million individuals worldwide have DM. By 2030, this number is projected to rise to 366 million (9), positioning the condition as one of the leading global causes of mortality, disability, and economic hardship. Diabetes develops when the body cannot adequately utilize or produce sufficient amounts of insulin, causing glucose in the blood to remain unable to enter cells for conversion into energy (10-19). This results in the onset of diabetic symptoms (20-27). Various factors such as obesity, genetics, race and ethnicity, age, medical history, smoking, nutrition, alcohol usage, and stress play a significant role in its development (27-39).

Early identification of diabetes poses a considerable challenge, and once it is detected, the condition cannot be reversed. Therefore, timely recognition of diabetes is vital to enable interventions that can delay or prevent the onset of type 2 diabetes. On the other hand, identifying individuals with prediabetes can lead to improved blood sugar control, reduced risk of complications, decreased economic burden, and an enhanced quality of life (40).

Various methods have been attempted to detect diabetes through blood and urine tests. Traditionally, the diagnosis of diabetes involves the Fasting Plasma Glucose (FPG) test, which requires a small blood sample from the patient after a 12-hour fasting period. This method is considered uncomfortable, invasive, time-consuming, and inconvenient. Urine tests for diabetes have also been conducted in hospitals, but they are time-consuming and relatively expensive, making them less efficient. Given these circumstances, there is a pressing need for innovative solutions that allow for easy, effective, and efficient diabetes detection (41).

The diagnosis of diabetes through facial features has the potential to serve as a cost-effective screening tool (42,43). Researchers have currently uncovered various methods for detecting DM by analyzing human facial features (43). Facial features result from the complex interplay of genetic information, bone structure, muscle composition, adipose tissue distribution, and other factors, all of which are in line with the pathogenesis of Type 2 Diabetes (T2DM) (44).

With the rapid development of Artificial Intelligence (AI), face recognition has attracted attention due to its status as the main method of human identification when compared with other types of biometric methods. Therefore, AI plays a critical role in face recognition technology, enabling systems to identify and verify individuals based on their facial features. It is essential for early detection and diagnosis, offers a non-invasive method, and provides cost-effectiveness, efficiency, and accuracy (45).

Face recognition technology, powered by sophisticated AI algorithms, leverages deep learning techniques, particularly Convolutional Neural Networks (CNNs), to enhance the precision and reliability of facial identification and verification. These AI-driven systems are capable of learning and recognizing intricate patterns and features in human faces, even in diverse conditions such as varying lighting, angles, and facial expressions. Research indicates that AI-based face recognition systems have surpassed traditional biometric methods, achieving higher accuracy rates and lower error margins (45,46).

In the healthcare, AI-driven face recognition technology plays a pivotal role in patient identification, ensuring accurate medical records and personalized treatment. It is also being explored for early diagnosis of genetic disorders by analyzing facial phenotypes, demonstrating the potential for innovative medical applications.

Given the rapid global increase in diabetes cases (46), it is imperative to identify pre-diabetic patients and individuals at higher risk for future diabetes development. With the potential of AI and facial recognition technology as non-invasive, cost-effective, and efficient alternatives for detecting diabetes, this study aims to improve early diagnosis and patient outcomes. Since there is limited information regarding the role of facial recognition in diabetes diagnosis, this research seeks to evaluate early detection of diabetes based on facial features using various AI approaches.

Facial recognition

The human face is a distinct marker of individual bio-identity, providing valuable insights into factors such as age, gender, race, consciousness, emotional state, and health status. Due to its accessibility and cost-effectiveness, facial recognition has gained widespread acceptance as a dependable biometric method, surpassing fingerprint and iris recognition. It is worth emphasizing that many diseases exhibit internal structural and functional abnormalities, as well as distinct facial characteristics and deformities (45).

Automatic facial recognition technology appeared in the 1960s, and over time, it has evolved into a pivotal tool with a wide range of real-world applications, including security surveillance, identity verification, forensic science, law enforcement, *etc*. (47). Pioneering research into the utilization of facial recognition for disease diagnosis began in the early 2000s, with initial successes in the identification of genetic syndromes in children (48,49) and the detection of facial neuromuscular dysfunction (50) through knowledge-based approaches. Recently, facial recognition-based diagnosis has emerged as a highly promising and innovative field within interdisciplinary medical practice.

Facial recognition enables effective screening in clinical practice, offering the potential for early diagnosis. Such an early detection proves highly advantageous for patients, facilitating prompt initiation of therapy and ongoing lifelong support.

The facial recognition system is employed for the evaluation of endocrine and metabolic disorders, genetic and chromosomal anomalies, neuromuscular ailments, and various other categories of diseases.

Influential Factors on the Face of Diabetic Patients

It seems that the main effects of diabetes on the face can be attributed to edema, oxidative stress, and craniofacial anomalies, damage of blood vessels and collagen.

Edema

Edema, the excessive accumulation of body fluids in interstitial spaces or body cavities is visibly evident on the faces of diabetic individuals. Edema results in puffiness around the eyes, leading to the characteristic swollen or compressed appearance of the average facial shape in individuals with diabetes (10).

Damage of blood vessels and collagen

Elevated glucose levels can have detrimental effects on blood vessels, leading to impaired circulation and reduced blood flow within the skin. This vascular damage can result in alterations to the skin's protein structure, particularly collagen, which is impacted by the diminished blood flow. Changes in collagen levels can significantly influence the skin's ability to heal its overall texture and appearance. Notably, these skin issues often serve as indicators of inadequate glycemic control.

Therefore, in individuals with diabetes, hyperglycemia can lead to impaired microcirculation, which can manifest clinically as visible deformities in facial veins. Consequently, diabetes can contribute to the development of various facial skin conditions, such as vitiligo, rubeosis faciei, Bell's palsy, and scleroderma (51).

Oxidative stress and impaired collagen production

Hyperglycemia can influence the activity of oxidases *via* both direct and indirect mechanisms, ultimately leading to the generation of oxidative stress. Mechanistically, oxidative stress stimulates collagen breakdown and inhibits collagen production. Oxidative stress and the presence of Reactive Oxygen Species (ROS) lead to an increase in the c-Jun/AP-1 transcription factor, multiple matrix metalloproteinases, and the degradation of collagen. Furthermore, oxidative stress and ROS contribute to the down-regulation of the TGF-β type II receptor and Smad3 proteins, resulting in impaired collagen production (52).

In addition, Advanced Glycation End products (AGEs), which is formed more quickly when blood glucose levels are elevated, produce ROS (53) through their primary signaling receptor, the AGE-specific receptor (sometimes shortened to RAGE). This causes proliferative, inflammatory, thrombotic, and fibrotic responses in a range of cells. This data demonstrates the role of AGEs in aging- and diabetes-related illnesses such complications from diabetic vascular disease (54). As a result, AGEs play important roles in the etiology of problems associated with diabetes.

Craniofacial Anomalies

The development of the craniofacial complex is influenced by a combination of genetic and environmental factors. Hormones, nutrition, mechanical stresses, and various local growth factors serve as regulatory mechanisms governing the normal development of the face and head (55).

Craniofacial Anomalies in Type 1 Diabetes

The peak growth period, which coincides with the onset of Type 1 Diabetes (T1DM) and during which approximately 60% of adult bone mass, including craniofacial bone, is acquired, has a significant impact on the process of bone formation. While the exact causes of T1DM are still unknown, it is essential to emphasize that understanding the disease's progression and its effects on craniofacial development may lead to advancements in oral health practices.

Investigating the alterations in craniofacial bone structure and the dynamics of bone formation under diabetic conditions is crucial for comprehending how diabetes influences various aspects of mandibular growth and bone quality (56). A comparison of craniofacial skeletal parameters in individuals with T1DM and a control group revealed that T1DM patients exhibit underdevelopment in most craniofacial skeletal and soft tissue aspects when compared to the control group. Consequently, diabetic patients display reduced skeletal maturation and cephalometric parameters (56).

Craniofacial anomalies in the fetus

Maternal diabetes can induce systemic metabolic changes that impact nearly every organ system, with the craniofacial, central nervous, and cardiovascular systems being the most commonly affected. These deformities, collectively referred to as diabetic embryopathy, are believed to stem from abnormalities in neural crest cell growth and neurulation during the early stages of organogenesis, typically occurring within the first 8 weeks of human gestation. "Neurocristopathies" is a term used to describe problems related to cranial neural crest cell production, migration, or differentiation that result in craniofacial deformities. Depending on when harm occurs during cranial neural crest cell development, distinct morphologies become apparent. Pregnant women with pre-gestational diabetes have a three-to-five times higher risk of giving birth to infants with birth abnormalities compared to women without diabetes (57). The significant likelihood that mothers with either Type 1 or Type 2 diabetes will have children with diabetic embryopathy points to hyperglycemia and increased glucose uptake by the embryo through glucose transporters as the primary causative factors (58).

The Mechanism of Hyperglycemia effect on Neural Tube Defects

Elevated oxidative phosphorylation and generation of ROS, stemming from excessive glucose metabolism lead to an oxidative stress condition (59,60). One of the negative effects of excess ROS is that it can disrupt key signaling events during cellular differentiation, resulting in structural abnormalities (61).

Hyperglycemia and epigenetic modifications can affect the pax3 downregulation, and TCOF1 down-regulation. Downregulation of TCOF1 (through intermediate signals) and pax3 down-regulation can lead to p53 activation. P53 activation *via* apoptosis and cell cycle arrest lead to neural tube defect. In addition, hyperglycemia *via* increased oxidative stress led to accumulation of DNA damage, p53 activation, cell cycle arrest, apoptosis, hypoplasia, neural tube defects (57).

Diabetic facial recognition

Diabetic facial recognition can be achieved using various methods. Some of these methods are done with emphasis on AI Top of Form

- Physical manifestations

In patients with DM, symptoms such as dehydration, ketosis, dry skin, and reduced skin elasticity can occur (62), but in most cases of DM, physical manifestations may be typically absent. It means that not all diabetic cases have facial clues indicating metabolic/diabetic condition.

Insulin-Dependent Diabetes Mellitus (IDDM) is also associated with increased glycosylation of skin collagen, which leads to the accumulation of rigid and less degradable collagen. Consequently, diabetic patients generally have thicker skin, especially on the face, compared to non-diabetic individuals. This increased skin thickness in diabetics may be a contributing factor to the less angular or rounder facial shape observed in these individuals.

The faces of diabetic patients often exhibit puffiness around the eyes, giving them a compressed appearance. General observations suggest that in male individuals with diabetes, there is a noticeable tapering towards the front of the face. On the other hand, females tend to have smaller nasal cavities and a gentler curvature just above the teeth. Notably, females typically lack a brow ridge, and their foreheads exhibit a more pronounced curvilinear shape (10).

Morphological Disorder-Based Procedures

Geometric morphometrics

Geometric morphometrics serve as a robust visual statistical tool (55) for the quantitative analysis of biological shape, its variations, and their relationships with other biotic or abiotic factors.

In the realm of biomedical and biological research, the analysis of an organ or organism's shape and size becomes more precise when utilizing landmarks. In the field of medicine, the geometrical properties of organs are intertwined with a variety of studies that rely on statistical analyses, employing qualitative and quantitative measures, particularly in the context of image analysis. In this approach, data is acquired through landmarks, whose points adhere to the rules of homology, signifying biological correspondence and ensuring reliable anatomical definitions. This homology among landmarks plays a pivotal role in securing a biologically interpretable outcome (58).

Geometric morphometrics have proven effective in identifying patterns associated with diseases, primarily through the description of facial shape. It can be instrumental in pinpointing specific health-related issues within the healthcare domain. Geometric morphometrics approaches are employed to explain the edema-related alterations on diabetes patients' faces. Diabetic individuals using partial warps may exhibit characteristics like right-sided asymmetry or elongation, brow ridge drooping, facial compression towards the center, and downward skin folding around the eyes (10). However, traditional morphometric measures such as linear distances, angles, and ratios have limitations in accurately quantifying the intricate geometry of specific anatomical structures (60).

Cephalometry

Cephalometry, introduced by Broadbent in 1931, ushered in a profound transformation in the diagnostic evaluation of facial forms and various craniofacial features. Lateral cephalograms, in particular, hold immense diagnostic and treatment planning significance. Linear and angular measure- ments obtained from lateral cephalograms play a pivotal role in the diagnosis and assessment of growth and developmental abnormalities. It is worth noting that while cephalometric analysis remains the gold standard for diagnosing skeletal craniofacial morphology in orthodontic clinical practice, it is an expensive and technique-sensitive procedure (63).

The cephalometric analysis for both Juvenile diabetes and control groups was shown and compared by Mushayat *et al* (56).

Moreover, cephalometry has general limitations (64).

- Cephalometry provides a two-dimensional view of a three-dimensional object, which can limit its accuracy.
- Landmark identification errors can occur, reducing the reliability of cephalometric analysis. Errors may arise during the tracing procedures.
- Assumptions play a significant role in cephalometric method: a) symmetry: analysis based on lateral projections assumes the absence of skeletal asymmetry in the patient. If asymmetry is present, the analysis results may be inaccurate. This can be mitigated by analyzing postero-anterior projections. b) Accurate occlusal and postural positioning is crucial for the cephalogram's accuracy.
- Fallacy of False Precision: When multiple cephalograms of the same individual are taken and traced, the measurement of various angles may show a standard error of 1:5, indicating slight variations with each measurement.
- Neglecting Patient Variability: Cephalometric values should not be treated as fixed goals, as individual patient differences can influence the results.

Artificial Intelligence (AI)

Since its inception in the 1950s, AI has been deeply committed to understanding human problem-solving approaches and integrating or simulating these strategies within computer programs (65).

AI is a branch of computer science that aims to create systems or methods that analyze information and allow the handling of complexity in a wide range of applications (in this case, diabetes management). Although the application of AI algorithms involves highly technical and specialized knowledge, this has not prevented AI from becoming an essential part of the technology industry and making contributions to major advances within the field (66).

AI-based automatic image recognition has the potential to identify image features for diagnosing and screening various diseases, demonstrating satisfactory performance in diagnosing certain diseases (46,47,67). AI has been widely applied in the analysis and identification of medical images, such as lung nodules, colon polyps, breast nodules, and ocular fundus (68). AI is a quickly growing field, and its applications to diabetes research are growing even more rapidly.

Moreover, AI-based facial recognition has recently played a crucial role in the diagnosis and screening of diseases characterized by facial phenotypes or changes (45,69). For instance, AI algorithms can detect subtle facial anomalies that may indicate genetic disorders, enabling early intervention and personalized treatment plans. This technology offers a non-invasive, efficient, and accurate method for medical professionals to enhance diagnostic processes and improve patient outcomes.

Overall, the integration of AI in medical image and facial recognition continues to revolutionize healthcare by providing advanced diagnostic tools, improving disease detection accuracy, and fostering innovative research avenues in fields like diabetes management and genetic disorder identification.

The most important AI-based facial recognition methods involve a combination of machine learning, computer vision, and deep learning algorithms. These techniques enable computers to identify and verify human faces from digital images or video frames:

Computer vision

Computer Vision is one of the most fascinating and challenging tasks in the field of AI. Computer Vision serves as a link between computer software and the visuals we see around us (70). A key goal of computer vision researchers is to create automated face recognition systems that can equal, and eventually surpass human performance. To this end, it is imperative that computational researchers know the key findings of experimental studies regarding face recognition by humans. These findings provide insights into the nature of cues that the human visual system relies upon for achieving its impressive performance and serve as the building blocks for efforts to artificially emulate these abilities (71).

Machine learning

Machine learning is a branch of computer science and has significantly advanced the field of facial recognition by enabling computers to learn and improve from experience without being explicitly programmed for each specific task. It is closely related to computational statistics and mathematical optimization (45,72). Machine learning uses algorithms that can learn from and make predictions based on data (73). The primary types of learning algorithms include (74,75):

- Supervised Learning: Involves training the system on a labeled dataset, meaning the data includes both the input (*e.g.*, facial images) and the correct output (*e.g.*, the identity of the person).
- Unsupervised Learning: The system is trained on data without labeled responses, aiming to find hidden patterns or intrinsic structures in the input data. Techniques such as clustering can be used to group similar faces.
- Semi-Supervised Learning: Combines a small amount of labeled data with a large amount of unlabeled data during training. This approach is useful when acquiring a fully labeled dataset is expensive or time-consuming.
- Reinforcement Learning: The system learns by receiving rewards or penalties based on its actions, refining its strategy over time to maximize the cumulative reward (6).

Machine learning methods can be applied in facial recognition systems to detect, align, recognize, verify, and identify individuals based on their facial features. Each step leverages specific machine learning techniques to achieve accurate and efficient facial recognition capabilities. In the following, a summary of each step in facial recognition is described (45,76,77).

- Feature Extraction: Machine learning algorithms automatically identify and extract relevant features from facial images, such as the distance between the eyes, the shape of the cheekbones, and the contour of the lips.
- Face Detection: The first step in facial recognition involves detecting the presence of faces in an image

or video stream. Machine learning models are used to locate faces with high accuracy.

- Face Alignment: This step involves transforming the detected face to a canonical pose, which standardizes the face for further analysis. Techniques like facial landmark detection help in aligning the face by identifying the key points (*e.g.*, corners of the eyes, tip of the nose).

- Face Recognition: The core task where machine learning models are used to match detected and aligned faces to a database of known faces.

- Face Verification and Identification

Verification: Determines if two faces belong to the same person. This is typically a one-to-one matching task.

Identification: Identifies a person from a list of known

Table 1. The studies regarding the role of AI in facial recognition in diabetes

Author (Ref no.)	Year	Area	Findings
Ting (81)	2014	DM identification with the Gabor Filter based on face Block Texture Features	Diagnosis of diabetes with 99.82% accuracy, 99.64% sensitivity, and 100% specificity.
Zhang (82)	2014	Non-Invasive DM detection through facial block color utilizing a Sparse Representation Classifier	Diagnosis of DM with an average accuracy of 97.54%
Zhang (83)	2016	Diabetes Identification Using Facial Block Color Features and Sparse Representation Algorithms	With 99.65% sensitivity, 97.93% specificity, and 99.06% accuracy, diabetes is diagnosed.
Padawale (43)	2016	Diabetes Detection according to Texture and Color Features of Facial Block	94.28% accuracy with k-NN and 97.14% accuracy with SVM classifiers were used to distinguish DM from a healthy patient.
Shu (85)	2017	Evaluation of different Texture Feature extractors for DM Detection in Facial Specific Regions	Diagnosis of diabetes with an accuracy of 99.02%, and sensitivity of 99.64%, as well as specificity rating of 98.26%.
Parvana (85)	2017	DM detection using the GLCM's Facial Texture Feature	Diagnosis of DM with 91.67% accuracy, sensitivity of 100% and specificity of 83.33%.
Shu (86)	2018	Non-invasive face block analysis method for detecting diabetes	Through facial key block analysis, the computer-assisted non-invasive diabetes mellitus detection system has demonstrated notable success and efficiency in real-time discrimination between diabetic patients and their healthy counterparts.
Li Zhang (87)	2018	Classification of multiple diseases using facial Image analysis and a Convolutional Neural Network	The proposed technique had an average accuracy of 73% based on three datasets that included healthy controls, those with diabetes, and people who had lung disease.
Garcia (88)	2019	Features of Facial Texture captured for non-invasive DM detection in a less restrictive environment	SVM-based DM diagnosis with 90% accuracy, 93% sensitivity, and 93% specificity.
Zhou (89)	2019	Facial Chromaticity and Texture Features for Non-invasive Disease Detection Using L-SRC	The average accuracy for detecting pre-diabetes was 74.31%. This offers a potential non-invasive screening technique to deal with future diabetes patients.
Zhu (42)	2020	A Face-based Progressive Stack Network for breast cancer and DM Detection	The results of the experiments indicated that the proposed approach had a 92.94% overall accuracy.

individuals. This involves a one-to-many matching task, where the input face is compared against all faces in the database.

Deep Learning Methods

Deep learning is a subset of machine learning that utilizes neural networks with multiple layers to learn from data and make predictions. Unlike traditional machine learning algorithms that require feature extraction and selection by humans, deep learning models automatically learn hierarchical representations of data directly from raw inputs. This capability makes deep learning particularly powerful for tasks involving complex patterns and large datasets (78-80).

In recent years, CNNs have become pivotal in facial recognition due to their enhanced accuracy. Deep learning, as a broader discipline, shows promise in reducing the influence of emotional variations and varying lighting conditions. Moreover, advanced deep learning algorithms have been developed to analyze video recordings capturing facial movements indicative of certain medical conditions.

Three-dimensional CNNs, an extension of traditional CNNs that process data from consecutive frames, are utilized to detect neurological disorders characterized by facial dysfunctions. Furthermore, cutting-edge deep learning architectures such as Long Short-Term Memory (LSTM) networks have been integrated with conventional classification techniques (45) to further enhance diagnostic capabilities

AI Techniques for Diabetes Diagnosis Using Facial Features

Advancements in AI techniques have facilitated diabetes diagnosis through facial features. However, there have been limited studies conducted on the role of facial recognition in diabetes using AI approaches. Some of the most important ones are mentioned (Table 1).

Conclusion

Diagnosis of diabetes is achievable through the analysis of facial features using various approaches. While diabetic face recognition can be performed by an experienced physician, the combination of simplicity, accuracy, and cost-effectiveness of AI procedures makes it a promising approach that contributes to advancements in pre-clinical diagnosis. Recent advancements in AI techniques for diabetes have substantially enhanced the accuracy of facial feature detection. Therefore, it seems that AI-driven facial recognition technology can be instrumental in identifying pre-diabetic individuals. Early identification of pre-diabetes allows for timely interventions, such as lifestyle modifications and medical management, which can delay or even prevent the progression to full-blown diabetes. This approach not only improves patient outcomes but also reduces the economic burden associated with diabetes management and complications.

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Conflict of Interest

There was no conflict of interest in this manuscript.

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