Smart Municipal Services and Predictive Healthcare: A Thermal Imaging Perspective

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Abstract: In the present day, diabetes is viewed as a serious problem. It can be promoted and campaigned as a smart municipal service to create awareness. The heart, nerves, eyes, and other human disorders, among others, might all be negatively impacted by this illness. Thus, early detection of diabetes patients is crucial to implement preventative treatments as soon as possible. In this work, a machine intelligence (MI) based approach is proposed for classifying diabetic and non-diabetic patients from the thermal image analysis of the human foot. This approach is focused on several machine learning (ML) models, such as k-nearest neighbour (KNN), decision tree (DT), AdaBoost (AB), and Naive Bayes (NB), to carry out such classification mechanisms. This study employs a cross-validation mechanism with the number of folds (NFD) set to 3, 5, and 10. By analysing the percentage of classification accuracy (CA) based on the dataset for different ML-based models, KNN achieved superior classification results than DT, AB, and NB, which are 93.30%, 94.60%, and 95.10%, for NFDs 3, 5, and 10, respectively.

Keywords: Diabetes, Machine Intelligence, K-Nearest Neighbour, Decision Tree, AdaBoost, Naïve Bayes, Classification Accuracy

I. Introduction

Diabetes mellitus (DM), often referred to simply as diabetes, is a medical condition defined by high blood sugar (glucose) levels [1-5]. It can be promoted and campaigned as a smart municipal service to create awareness. It arises when the body either fails to produce enough insulin, does not produce it, or becomes resistant to insulin's effects. Glucose, or sugar, primarily comes from the carbohydrates in food and beverages [6, 7]. Diabetes can impact individuals of all ages and is usually a chronic condition. While it can be managed through medication or lifestyle adjustments, sustained high blood sugar can result in severe complications, such as cardiovascular disease, nerve damage, and vision loss [8-10]. Diabetes is classified into various types, including diabetes, prediabetes, gestational diabetes, latent autoimmune diabetes in adults (LADA), maturity-onset diabetes of the young (MODY), neonatal diabetes, and brittle diabetes [1, 5, 11]. Blood glucose levels are typically measured using three key tests. (1) Fasting blood glucose test: This test requires fasting for at least eight hours, consuming only water before the test. (2) Random blood glucose test: This test can be taken at any time, regardless of fasting status. (3) A1c test: This test provides an average of blood glucose levels over the past two to three months [3, 6].

According to reports, in 2019, 463 million people worldwide were living with diabetes, and projections estimate that this number will rise to 578 million (10.20% of the global population) by 2030 and 700 million (10.90%) by 2045. While genetic forms of diabetes cannot be prevented, several measures can help reduce the risk of developing prediabetes, type 2 diabetes, and gestational diabetes, such as adopting a healthy, plant-based diet, engaging in regular physical activity, managing stress levels, limiting alcohol consumption, ensuring sufficient sleep, quitting smoking and taking prescribed medications [2, 3, 8].

The main features of this study are outlined as follows. (1) This work focuses on an ML-based strategy for classifying diabetic and non-diabetic patients using thermal imaging of the human foot. (2) Various ML models, such as KNN, DT, AB, and NB, are employed in this classification method. Cross-validation is applied using NFD values of 3, 5, and 10. (3) The ML models are compared based on their CA. (4) The results indicate that KNN outperforms the other models. (5) The study is conducted using the Orange platform, which is Python-based.

The remainder of the paper is structured as follows. Sections II, III, IV, and V cover the related works, methodology, results and discussion, and conclusion, respectively.

II. Related Work

The background study on diabetes is described as follows [1-16]. DM is a metabolic disorder distinguished by persistent hyperglycemia and greater or lesser impairment in glucose, lipid, and protein metabolism [1]. Diabetes is the medical word for DM. High blood sugar is a metabolic disease in this group [2-4]. Diabetes can result in a variety of serious, long-term, and complex problems, including blood vessel and nerve damage, peripheral artery disease, renal failure, heart attack, and cardiovascular disease [5, 6]. There were around 122 million diabetics worldwide in 1980; by 2014, there were approximately 422 million [7]. By 2040, the population will be at 642 million. The number of diabetic people is increasing daily, which means that mortality is rising as well. Diabetes is classified into three types: type I diabetes (T1D), type II diabetes (T2D), and gestational diabetes (GD) [8]. Type II DM (T2DM) is exceedingly common and causes significant morbidity and mortality. Furthermore, it has a substantial financial impact on individuals/families, healthcare systems, and governments. The fact that T2DM incidence and prevalence are rapidly increasing is quite worrying. According to projections, diabetic rates will significantly increase in the coming year by 2045, with a 48% increase in prevalence from the numbers above, or an estimated 629 million people (approximately 6.60% of the global population) who have diabetes. In 2017, it was predicted that 425 million individuals have diabetes (about 5.50% of the global population), with 90000 deaths.

Before the age of 35, type I DM (T1DM) clinically manifests. Hyperglycaemia, which is brought on by this form of diabetes and can result in higher blood glucose levels, can lead to other issues. Insulin must be given to prevent complications, such as dehydration and death. Maintaining a healthy amount of insulin is essential for managing T1DM. Automated blood glucose regulation in diabetic individuals can prolong their lives and lower treatment costs [14, 15]. In diabetic individuals, diabetic foot (DF) is a prevalent condition that often results in foot ulcerations, which is the leading cause of most foot amputations. Diabetes experts believe that by considering thermal information, which is now not done in the clinical routine, ulcer occurrence can be decreased even more. An infrared camera can be used to detect temperature differences that are related to diabetes foot [9-11]. An infrared camera is a fast, painless, cost-effective, non-invasive, and contactless method that enables the visualization and accurate measurement of temperature distribution. Thermography for DF imaging is becoming increasingly popular [12]. During the process, the patient places their feet in specialized equipment that eliminates all thermal sources except those from the plantar foot. The thermal camera captures images, which are then sent to a computer for analysis. This method ensures that the background of the plantar foot remains uniform, and the infrared image focuses solely on the surfaces of the plantar foot [16].

III. Methodology

Those who have diabetes and those who don't can be classified using various methods. The classification of diabetes and non-diabetic patients from the thermal image analysis of the human foot is the primary goal of this work. The ML-based techniques, KNN, DT, AB, and NB, which are discussed below, are the main emphasis of this work.

(1) KNN is a simple supervised ML model used for classification and regression tasks. It operates on the premise that data points closest to one another are likely to be similar, allowing for the classification of new points based on the values of their nearest neighbours. Although KNN is based on distance calculations, it can be inefficient because calculating the distance between each current point and a new point is computationally expensive.

(2) DT is a graphical model representing potential solutions to a problem involving conditional decisions. In this supervised learning method, data is repeatedly split according to specific criteria. The tree consists of decision nodes and leaf nodes. Decision nodes make decisions and branch out into various paths, while leaf nodes represent the outcomes of those decisions and do not have further branches. The structure of a decision tree resembles a tree, starting from a root node and growing outward as more branches are added.

(3) AB is an ensemble ML method that enhances the performance of binary classifiers, often using DTs with a single split, known as decision stumps. It is initially designed to improve weak classifiers. AB works by iteratively refining them based on the errors they make. Each classifier is trained on the same dataset but with weights adjusted to emphasize misclassified instances, allowing subsequent classifiers to focus on the more challenging cases. This approach reduces the likelihood of overfitting and can enhance the accuracy of weaker classifiers. AB is applied to binary classification and is now used to classify text and images.

(4) NB is an efficient method for developing ML models that prioritize quick predictions while maintaining accuracy. It applies statistical probability to handle discrete data, which helps analyze and predict outcomes. NB is particularly effective at managing large datasets with multiple features and properties.

The workflow is outlined in Fig. 1. Initially, thermal images of the human foot are input into Python via Orange 3.26.0. Image embedding techniques are then applied to extract essential features like width and height. The test and score mechanism is used to evaluate the CA of the KNN, DT, NB, and AB models. The confusion matrix (CM) visualizes the CA values by comparing the actual and predicted instances.

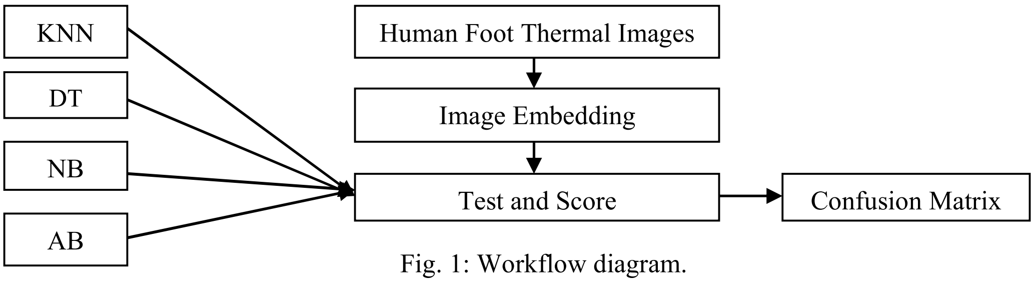

Fig. 1: Workflow diagram.

IV. Results and Discussions

In our work, 1428 human foot thermal images with 714 diabetic and non-diabetic cases each are taken from the source for processing [18]. Python-based Orange 3.26.0 is used for this work [17]. These images are processed using ML-based models like KNN, DT, AB and NB. A performance metric (i.e., CA) is used to evaluate these models. The Orange workflow diagram is mentioned in Fig. 2. The human foot diabetic and non-diabetic image samples are mentioned in Fig. 3 and Fig. 4, respectively.

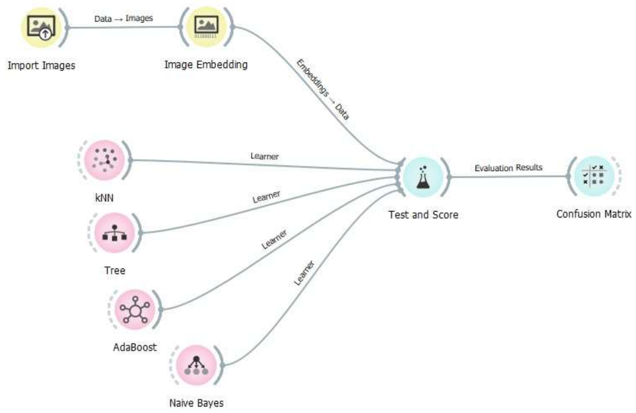

Fig. 2: Orange workflow diagram.

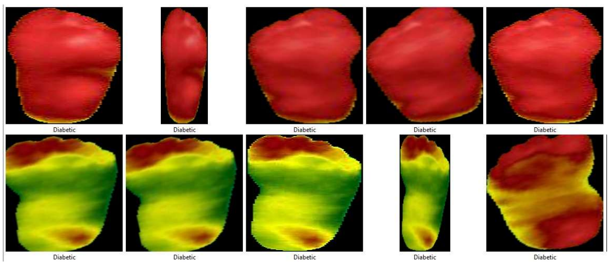

Fig. 3: Diabetic cases human foot thermal images.

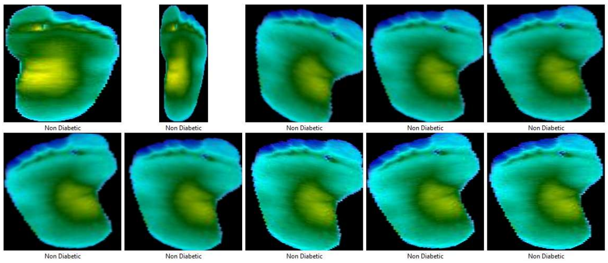

Fig. 4: Non-diabetic cases human foot thermal images.

We consider three cases: NFD = 3, NFD = 5 and NFD = 10. The cross-validation mechanism with these NFDs is considered for processing several images. Table 1 describes the CA values of four models, KNN, DT, AB, and NB, at NFD = 3, NFD = 5 and NFD = 10. The CM for KNN, DT, AB and NB are mentioned in Table 2 for all the cases. Table 1 shows that the CA percentages for the KNN, DT, AB, and NB models at NFD = 3 are 93.30%, 88.30%, 87.30%, and 78.40%, respectively. At NFD = 5, the CA percentages for these models are 94.60%, 89.20%, 88.30%, and 78.40%, respectively. At NFD = 10, the CA percentages are 95.10%, 88.70%, 88.10%, and 78.20%, respectively. The KNN model consistently outperforms the DT, AB, and NB models at NFD = 3, NFD = 5, and NFD = 10. In contrast, the NB model consistently shows lower performance compared to KNN, DT, and AB. In all the cases, the models rank in performance as KNN, DT, AB, and NB in descending order.

Table 1: CA of four models at NFD = 3, NFD = 5 and NFD = 10

Model	CA (in %)		
	NFD = 3	NFD = 5	NFD = 10
KNN	93.30	94.60	95.10
DT	88.30	89.20	88.70
AB	87.30	88.30	88.10
NB	78.40	78.40	78.20

Table 2: CM of four models at NFD = 3, NFD = 5 and NFD = 10

CM for KNN at NFD = 3					CM for KNN at NFD = 5					CM for KNN at NFD = 10				
	Predicted					Predicted					Predicted			
Actual		Diabetic	Non-diabetic	∑	Actual		Diabetic	Non-diabetic	∑	Actual		Diabetic	Non-diabetic	∑
	Diabetic	630	84	714		Diabetic	642	72	714		Diabetic	646	68	714
	Non-diabetic	11	703	714		Non-diabetic	5	709	714		Non-diabetic	2	712	714
	∑	641	787	1428		∑	647	781	1428		∑	648	780	1428
CM for DT at NFD = 3					**CM for DT at NFD = 5**					**CM for DT at NFD = 10**				
	Predicted					Predicted					Predicted			
Actual		Diabetic	Non-diabetic	∑	Actual		Diabetic	Non-diabetic	∑	Actual		Diabetic	Non-diabetic	∑
	Diabetic	625	89	714		Diabetic	616	98	714		Diabetic	626	88	714
	Non-diabetic	78	636	714		Non-diabetic	69	645	714		Non-diabetic	82	632	714
	∑	703	725	1428		∑	685	743	1428		∑	708	720	1428
CM for AB at NFD = 3					**CM for AB at NFD = 5**					**CM for AB at NFD = 10**				
	Predicted					Predicted					Predicted			
Actual		Diabetic	Non-diabetic	∑	Actual		Diabetic	Non-diabetic	∑	Actual		Diabetic	Non-diabetic	∑
	Diabetic	620	94	714		Diabetic	621	93	714		Diabetic	619	95	714
	Non-diabetic	87	627	714		Non-diabetic	61	653	714		Non-diabetic	67	647	714
	∑	707	721	1428		∑	682	746	1428		∑	686	742	1428
CM for NB at NFD = 3					**CM for NB at NFD = 5**					**CM for NB at NFD = 10**				
	Predicted					Predicted					Predicted			
Actual		Diabetic	Non-diabetic	∑	Actual		Diabetic	Non-diabetic	∑	Actual		Diabetic	Non-diabetic	∑
	Diabetic	514	200	714		Diabetic	515	199	714		Diabetic	514	200	714
	Non-diabetic	108	606	714		Non-diabetic	110	604	714		Non-diabetic	111	603	714
	∑	622	806	1428		∑	625	803	1428		∑	625	803	1428

V. Conclusion

This study utilized various ML models, including KNN, DT, AB, and NB, to analyze thermal images of the human foot for classifying diabetic and non-diabetic patients. Moreover, this study aims to create awareness among the public as a smart municipal service. A cross-validation approach was employed with 3, 5, and 10 NFD values. The CA was used to assess and compare the performance of these models. The results indicate that KNN outperforms DT, AB, and NB in accurately classifying diabetic and non-diabetic patients based on thermal foot images. The CA values for KNN were 93.30%, 94.60%, and 95.10% at NFDs of 3, 5, and 10, respectively, with an average CA of 94.33%. Future work could focus on refining strategies to further enhance CA values under various conditions and expand the analysis to include additional ML models for comparison.

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