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Segmentation and Classification for Hyperspectral Imaging of Foot Inspection in Vascular and Neuro Images

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ABSTRACT

Diabetes Mellitus (DM) and Diabetic Neuropathy (DN) are the most common diseases in the worldwide, according to the World Health Organization (WHO). A high index of death is also correlated with it. Diabetic neuropathy is a significant worldwide cause of neuropathy which can lead to amputations and disabilities. Diabetic neuropathy can have multiple clinical manifestations, the most common presentation being distal symmetric polyneuropathy and the key mechanism for diabetic foot development. One of the major problems is diabetic foot, which includes the creation of plantar foot hyper spectral which may result in amputation. Several studies report that hyperspectral is helpful in identifying differences in plantar temperature, which may lead to a higher risk of ulceration. However, in diabetic patients, the distribution of plantar temperature does not follow a standard sequence, thereby making it impossible to quantify the changes. There is also an importance in enhancing the performance of the methods of analysis and classification that help to diagnose abnormal variations in the temperature of the plantar. All this refers to the use of computer-aided programmes that work with extremely structured data structures, such as those involved in artificial intelligence (AI). This study combines approaches based on machine learning with Deep Learning (DL) structures. Furthermore, we developed a new DL-structure, which is qualified and is able to achieve higher significance in terms of precision and other quality metrics. The key purpose of this study is to examine the use of AI and DL for the classification of hyperspectral images of the diabetic foot, demonstrating its advantages and disadvantages. To the best of our understanding, this is the first suggestion for the definition of diabetic foot hyperspectral implemented by DL networks. The studies are carried out in DM and control groups through hyperspectral images. Afterwards, based on a pre-reported hyperspectral shift index, a multi-level classification is done. The high precision attained illustrates the utility of AI and DL as auxiliary instruments to help in medical diagnosis. The aim of this study was to perform a systematic and updated analysis of diabetic neuropathy, concentrating on its classification, diagnostic research and treatment.

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KEYWORDS: *Machine Learning, Support vector machine (SVM), K-nearest Neighbors (KNN), Decision Tree Algorithm*

I. INTRODUCTION

Diabetes is a major global disease that affects 194 million people worldwide and is expected to increase in prevalence to 344 million by the year 2030 (1). One major complication of diabetes is foot ulceration, which occurs in as many as 15–25% of type 1 and type 2diabetic patients over their lifetimes (2–4). Studies show that between 2 and 6% of diabetic patients will develop a foot ulcer every year (5,6). The feet of patients with diabetes are at risk for ulceration due to a wide range of pathological conditions, the major three being peripheral neuropathy, foot deformity, and trauma, which may be exacerbated by comorbid peripheral vascular disease (4,7). If left untreated, foot foot hyper spectral lead to infection and deep-tissue necrosis (8). Foot pathology is a major source of morbidity in patients with diabetes and is a leading cause of hospitalization. Infected and/or ischemic diabetic foot foot hyper spectral (DFUs) account for about 25% of all hospital visits among patients with diabetes. Previous studies have shown that a DFU precedes roughly 85% of all lower extremity amputations in patients with diabetes (9,10), and more than 88,000 amputations are performed annually ondiabetic patients (11). The cost to manage foot disorders is estimated at several billion dollars annually (5,12). Successful clinical management of DFUs not only has the potential to reduce the cost of caring for these patients but also to improve quality of life by reducing comorbidities. Current treatment options for DFUs include offloading to reduce pressure onthe wound, wound care to prevent infections, and wound debridement to remove necrotic debris and restimulate the wound healing process (11,13,14). Even with these measures, some wounds fail to heal. Having a means to assess healing potential may help triage wounds earlier to more aggressive therapies, thereby avoiding infections and amputations.

Clinical measurements of microvascular function may be an important part of DFU assessment (15–17). Hyperspectral imaging (HSI) was developed as a novel noninvasive diagnostic tool to quantify tissue oxygenation and generate anatomically relevant maps of microcirculatory changes seen in diabetic patients (18). HSI generates a map of regions of interest based on local molecular composition. With proper wavelength selection, spatial maps of molecules such as oxyhemoglobin (oxy) and deoxyhemoglobin (deoxy) can be acquired. A pilot study of 10 type 1 diabetic patients with 21 DFU sites showed that HSI identified changes in tissue oxygenation in the diabetic foot that were predictive of ulcer healing (18). The sensitivity, specificity, and positive predictive value of the healing index were 93, 86, and93%, respectively.

A heterogeneous collection of pathological or subclinical symptoms involving the peripheral nervous system (PNS) as a symptom of diabetes mellitus is diabetic neuropathy (DN) (DM). It can have multiple clinical signs, pathways of pathophysiology, initiation and evolution1,2. DM was recognized as the cause of peripheral neuropathy only in 1864 (PN). Some years back, the presence of diabetic patients' cranial nerves was observed3. Bouchard described the deterioration of tendinous reflexes in the lower limbs (LLll) in 18844, and Pavy described the presence of involuntary symptoms such as pain and hyperesthesia in 18855. Buzzard registered motor manifestations in 18906. Leyden (1893)7, which subdivided it into sensory and motor manifestations, proposed the first DN classification. In turn, the first to mention pathophysiologic DN pathways were Jordon and Crabtree (1935)8.The prevalence of DN has dramatically improved after diabetic patients began to have longer life expectancy since the discovery of insulin in the 1930s to treat DM. Fagerberg9, Mulder et al.10 and Pirart, Lauvaux and Rey11 experiments have shown that DN is associated with other microvascular complications such as diabetic nephropathy and retinopathy12. The incidence of DN continues this rise in the face of an alarming number of DM patients and is now emerging as a major cause of NP in developed countries. It should be stressed that, as the most common micro-vascular complication, at least half of diabetic patients are expected to experience this neuropathy at some stage in their clinical development13. The most common clinical diagnosis of Distal symmetrical polyneuropathy is usually asymptomatic14.There is a form of neuropathic symptom in fewer than half of patients, most of them auditory symptoms [15]. Around 20% of DN patients have neuropathic pain, indicating a major de-crease in quality of life and mental capacity [16].

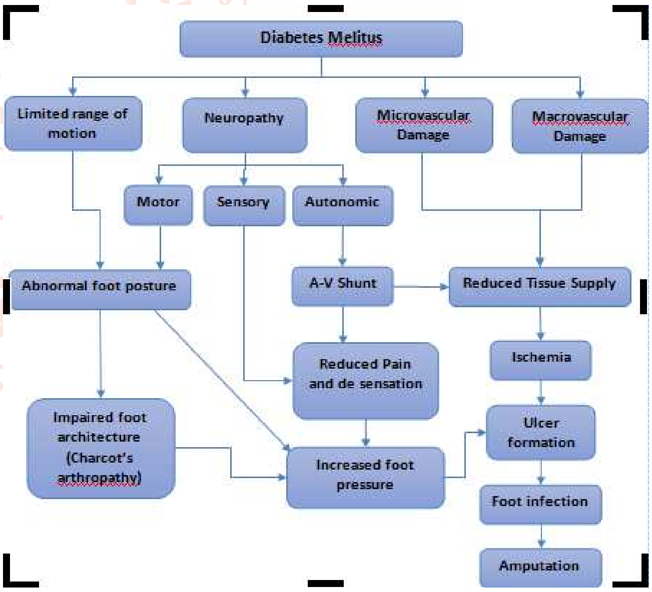


Fig 1: Hyper spectral Image Architecture

Complications, including heart problems, vision loss, organ failure, and inferior limb amputations. Such challenges not only impair the wellbeing of patients, but also have a huge effect on their personal and professional lives. One of the major risks is diabetic feet. Sensitivity failure in the diabetic foot, along with mechanical stress in the plantar region, has been reported to raise the risk of foot infection, which can lead to amputation. It is also established that a rise in temperature is associated with a higher risk of ulceration in the plantar area of diabetic patients. The interest in temperature control has also often emerged across various methods.

II. Related Works

In general, CAD systems are divided into offline and online methods. Most of these CAD programmers follow an offline procedure consisting of preprocessing images, collecting specific characteristics, evaluating statistical techniques, assessing highly significant characteristics, and eventually classifying them either using certain manual techniques (such as thresholding or point-to-point mean difference technique) or using intelligent computational methods (like Artificial Neural Networks or Fuzzy Logic). In computer-aided diagnostic systems, image segmentation and feature extraction are two key steps. Choosing the right segmentation strategy and extracting the necessary characteristics will improve the precision of CAD systems. To separate the plantar area from the context, scientific literature records multiple thermogram segmentation procedures. Five classes of auto-thresholding techniques, namely histogram shaped-based methods, clustering-based methods, entropy-based methods, entity attribute-based methods. They adopted an Active Contours Without Edges (ACWE) method; however, manual correction was still required for the images without good brightness and clear areas of the ankles and legs. The findings revealed that the technique of edge detection was more effective than that of the watershed system. To separate the plantar area from thermo grams, the CNN algorithm is used. On all purposes, the snake algorithm helps to isolate the feet from the context and, according to their temperature, to separate the right foot from the left one into various segmented clusters.

In plantar thermograms, image segmentation techniques may also play a critical role in isolating the hottest area, which can be used to extract specific characteristics. A hot area may be a symptom of tissue injury or inflammation in diabetic subjects. Lazy snapping is an immersive image algorithm that quickly distinguishes coarse and fine scale processing, achieving object state and thorough modification. Furthermore, lazy snapping offers immediate visual feedback, easily distinguishing the broken contour from the exact object border, independent of the presence of low contrast edges. To remove the hottest temperatures from the plantar zone, the authors used a histogram-shape dependent thresholding tool. After that, they developed a function vector centered on the components of the morphological pattern continuum, including a location criterion. The plantar region was divided into six areas and features were extracted, such as similarity, mean change of temperature, contrast and homogeneity, among others. A CAD method where the segmented images are sent to the techniques of discrete wavelet transformation (DWT) and higher order spectra (HOS), and then multiple coefficients are derived from the texture and entropy features. Using t-values, the extracted features are graded and categorised using an SVM classifier. They have a double density-dual tree-complex wavelet transform (DD-DT-CWT) to evaporate the image in a corresponding work.

In applications that include pattern recognition, detection, automated process control, among others, the use of computational intelligence algorithms (CI) has been successfully expanded. Among the methodologies of black-boxes, ANN is considered to be the most common one, where in the prediction of DM the vast majority of the published article achieves an accuracy of 80%. SVM, the most efficient algorithm in both biological and clinical data sets in DM is an alternative that has increased this degree of precision. The explanation for this is that ANN uses weight updating methods based on derivatives, which are subject to a sluggish convergence rate and therefore have sub-optimal solutions.

The use of large neural structures to learn at many layers of abstraction is another excellent approach that has gained relevance; it is called Deep Learning. In some tasks of DM's foot grouping, we can now list several linked works using CI methodologies. The paper contrasts algorithms, such as Logistic Regression (LR), ANN, Random Forest, and k-NN, after listing a variety of different types of DM and examples of data. We would like to stress that an algorithm's accuracy depends on the type of information (dimensionality, origin, and type); SVM, however, is the most efficient and commonly used classifier checking the algorithm in the Pima Indians Diabetes database, providing effective class boundaries. Finally, we can infer that DL techniques are permeating and strengthening conventional methods in the field of medical imaging, including examination, diagnosis, identification, classification, and segmentation. And without assistance of an expert, there are always difficulties to be faced, such as automated annotation to delineate and label the photos. Other problems include multi-class grouping, as well as enhancement of automated classifiers for, among others, disease identification, recognition, segmentation, and tracking.

III. Problem Statement:

Non-invasive techniques provide information on macrovascular anatomy, as well as on functional parameters concerning vessel flows, tissue perfusion, microcirculation, all of which are affected by complications concurring in the high morbidity and mortality on diabetic patients. Ultrasonography is mainly used to assess the atherosclerotic burden in non-coronary arteries. Doppler US has been successfully employed for an early and accurate characterization of the vasculopathy of lower limb arteries (a strong risk factor in the development of diabetic foot foot hyper spectral), thus favoring the prevention or delay of foot complications, especially amputation. Moreover, the measurement of the carotid intima-media thickness (IMT) by US has been demonstrated a useful marker of the progression of atherosclerosis throughout the body, and an excellent predictor of cardiovascular events even in diabetic population. Furthermore, carotid IMT can be used to evaluate the efficacy of new treatments.

At present, techniques based on CT technology, such as coronary artery calcium scoring and coronary multi-slice CT angiography, are considered the most robust imaging techniques for non-invasive visualization of coronary atherosclerosis, assessment of plaque composition and level of calcification. Also MRI is emerging as an important modality to assess atherosclerotic plaque burden and morphology in non-coronary arteries. Nevertheless, because altered vessel morphology may be ambiguous, the ability to non-invasively evaluate molecular and cellular pathological processes becomes crucial in terms of early detection and preventive treatment. The use of functional and molecular imaging approaches will provide valuable diagnostic tools. Recently, by using MRI in experimental studies on rodent diabetic models, Medarova*et al* evaluated pancreatic vascular volume, microvascular flow, and permeability that are common disease biomarkers for both T1D and T2D

Table 1 Relevant features of the most common imaging modalities

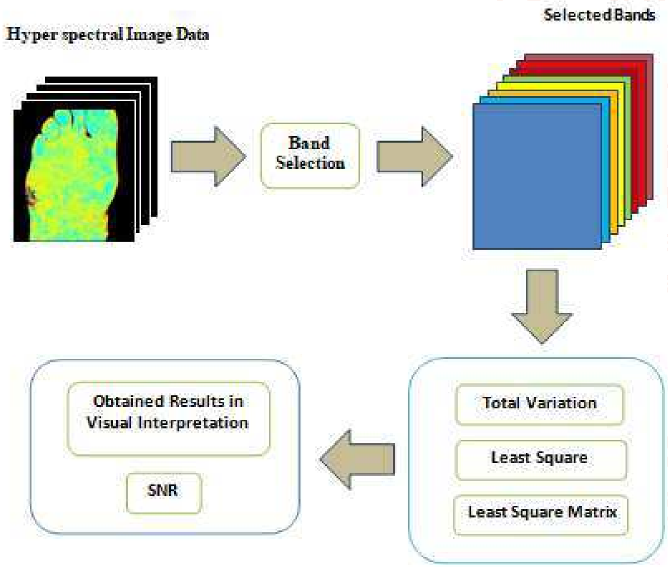
Imaging modality	Anatomy	Metabolism / function	Spatial resolution	Weakness
Single-photon emission computed tomography	Poor	Yes	0.3-3 mm	Radiation
Positron emission tomography	Poor	Yes	1-4 mm	Radiation
Computed tomography	Yes	Yes	0.5-1 mm	Radiation
Magnetic resonance imaging	Yes	Yes	50-500 µm	Expensive
Ultrasound	Yes	Yes	Approximately 200 µm	Poor depth penetration
Optical	Poor	Yes	0.1-10 mm	Poor depth penetration

Lower extremity and particularly foot foot hyper spectral are among the most frequent complications of diabetes. It is estimated that 15%-25% of T1D and T2D patients are affected by skin foot hyper spectral in their lifetime. Factors as peripheral neuropathy and vascular disease contribute to the development of skin ulcerations. Some valuable information on vasculopathy can be provided by Doppler US examination in patients with diabetic foot. Moreover, in the last few years hyperspectral imaging (HIS) has been launched as a useful diagnostic tool to monitor microvascular changes and tissue perfusion impairment associated with diabetic ulcer formation and healing. By selecting proper wavelengths within the visible and very near infrared region (400-1000 nm) of the electromagnetic spectrum, HIS allows to acquire spatial maps of oxy- and deoxyhemoglobin and, thus, to quantify tissue oxygenation. In the management of diabetic foot foot hyper spectral, it represents a valuable tool in the assessment of wound healing potential and in guiding the proper therapy in order to prevent infections and amputations. If left untreated, a relevant cases of foot foot hyper spectral lead to infection, limited joint mobility, muscular alterations and deep-tissue necrosis. Bones may also be involved in two different clinical conditions associated with diabetic complications, such as osteomyelitis and Charcot osteoarthropathy. The former is mainly due to direct bone contamination from a soft-tissue ulcer and accounts for approximately one third of diabetic foot infections, whereas the latter is a chronic and progressive inflammatory disease affecting the bone and joints. Both osteomyelitis and Charcot foot are conditions with an increased risk of lower limb amputation from 25% to 50%. It has been suggested that about 50% of those amputations could be avoided by an early diagnosis and a multidisciplinary approach. The major diagnostic difficulty is in distinguishing osteomyelitis from non-infectious bony disorders as Charcot foot.

X-ray planar radiographs are relatively inexpensive and readily available, but their sensitivity is quite poor and false negative results are not so rare, especially in the first stages of osteomyelitis. Bone biopsy is considered the technique of choice for detection of osteomyelitis, however conventional imaging (MRI, SPECT and hybrid SPECT/CT) are valuable support in the early diagnosis of infections and their accurate anatomical localization. In addition, due to their non-invasive nature, imaging studies proved particularly useful in monitoring the progression of the disease and the efficiency of specific treatments.

IV. Implementation:

This section outlines all the steps taken to achieve a final comparison of the above-mentioned machine learning-based classifiers. Collecting the hyperspectral images of DM subjects collected from a public archive of hyperspectral were used for the purposes of this work [53]. In additional to the further extraction of relevant features, a method of selection of the region of interest (ROI) for segmentation is necessary in order to use the MLP and SVM algorithms. In this case, with an evolutionary optimization strategy, we use a histogram-based segmentation approach represented by fuzzy sets and configured. In this section, this method is briefly described, but at the end of the work, it is extended in the appendices. Finally, the definition of the two-machine learning-based classifiers and the new DL structure suggested are briefly described.



Data Collection:

Studies were performed according to a uniformed study protocol that was approved by the institutional review boards at each center. After receiving a description of the protocol and asking questions, all patients agreeing to participate signed an approved informed consent form. Medical and family histories were collected from each patient. Clinical evaluation included age, sex, ethnicity/race, weight, height, BMI, systolic and diastolic blood pressure, ankle brachial index (ABI), A1C, diabetes type, and diabetes duration. Neuropathy was graded according to the Neuropathic Symptom Score and Neuropathy Disability Score (NDS).Transcutaneous oxygen tension (tcPO2) was measured at the ankle of both legs using a transcutaneous oxygen monitor (Model PF-5000; HTOM and skin temperature at the center of the image were collected with a commercial HSI system. The HSI system obtains multiple images at discrete wavelengths, providing a diffuse reflectance spectrum for each pixel in the image. The system uses wavelengths between 500 and 660 nm to include oxy and deoxy absorption peaks. Tissue oxygenation images or maps were constructed from oxy and deoxy values determined from each pixel in the image. Skin temperature was monitored with an infrared remote temperature sensor.

Prior to imaging, the system was calibrated to a reflectance card. Patients were imaged supine on a standard examination table or in a reclining chair and were allowed to rest for 10 min to minimize systemic vascular effects. Dorsal foot and peri wound tissues were imaged. A fiducial target was placed to facilitate image realignment correcting for patient movement. Image registration, processing, and quality assessment were conducted following the procedure. For wounds larger than 1 cm in diameter, mean oxy and deoxy values were extracted from a 1-cm radial border consisting of intact skin in the peri wound region while avoiding any hyperkeratotic tissue. For wounds less than 1 cm in diameter, a 0.5-cm border was used.

Spectral decomposition was used to extract relative values of tissue oxy and deoxy from the diffuse reflectance spectra by comparing with standard transmission spectra from solutions. Oxy and deoxy units represent relative concentrations of oxy and deoxy found in the tissue volume measured by the HSI system (approximately the effective pixel size of the object multiplied by the penetration depth of light into tissue [1–2 mm in this wavelength range]).

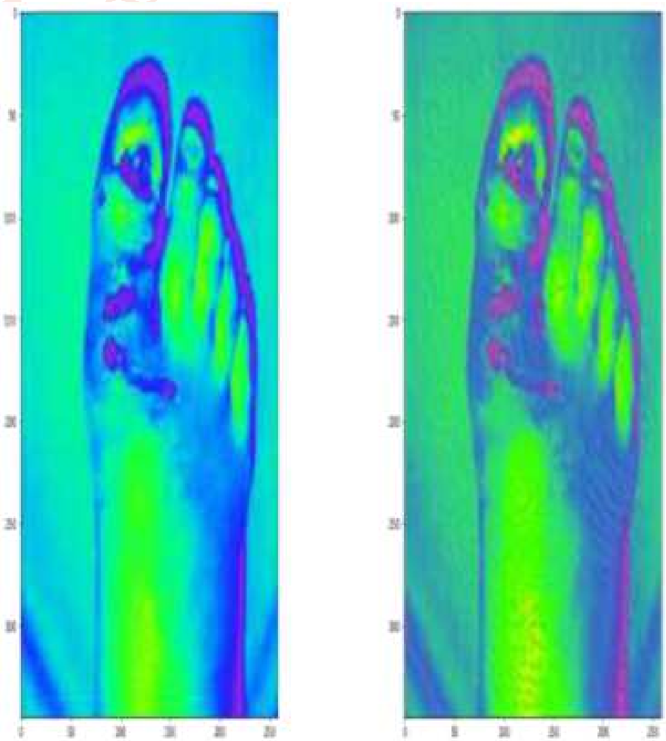


Fig 2: Hyper spectral foot Image

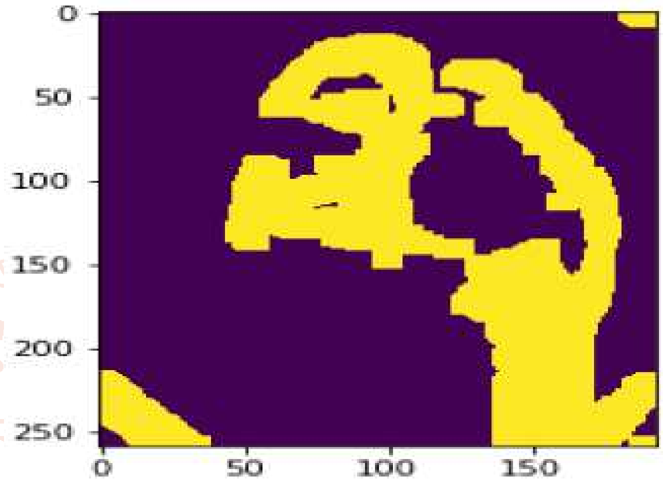
Tissue oxygen saturation, the fraction of oxygenated hemoglobin in superficial (predominantly subpapillary plexus) blood vessels, was calculated as the percentage of oxy over the sum of oxy and deoxy. Disease are classified into one of two groups: foot hyper spectral that healed within 24 weeks or foot hyper spectral that did not heal within 24 weeks. Foot hyper spectral with complete reepithelialization and no exudates at the last visit (24 weeks) were classified as healed. A healing index was then derived to best separate healed from no healed foot hyper spectral. The healing index was calculated as the distance between the point defined by the oxy and deoxy values and the linear discriminant decision line that best separated healed foot hyper spectral from no healed foot hyper spectral. A positive healing index was more likely to heal, whereas a negative healing index was more likely not to heal. Patients received regular care by their doctors, including offloading and debridement when required. The treating physicians were blinded to the HSI data. No criteria for wound size or duration were used to select patients. Clinical and HSI data were captured on case report forms and uploaded into a central database and central file server, respectively.

Data Pre-processing

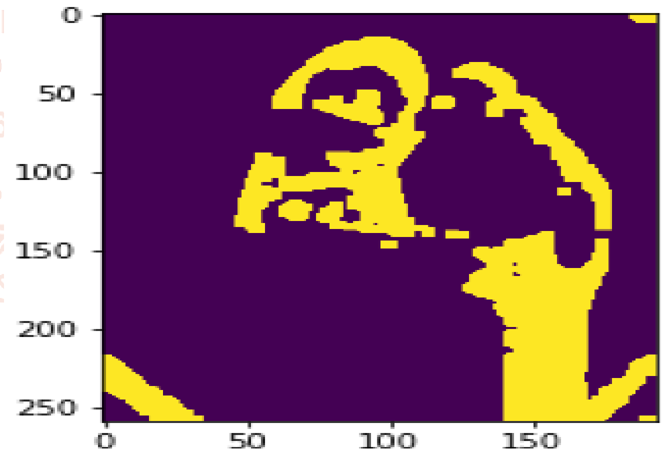
When DL structures are learned from scratch, because of the immense number of parameters trained in them, they require a huge number of images. Augmentation of data is an inexpensive approach for collecting such a quantity of data when we do not have it available. A mixture of different processing methods, such as rotating, flipping, contrast enhancement, using various colours, space, and random scaling, involves of data augmentation. Rotation is carried out at angles of 90x, 180x, and 270x in this job. We used three ways of flipping conducted on the initial patches (horizontal flip, vertical flip, and horizontal + vertical flip). We also obtained multiple patches of each image, enabling us to tenfold increase the data collection. The hyperspectral images shift groups which can be identified in the database and an illustration of the patches removed.

Segmentation

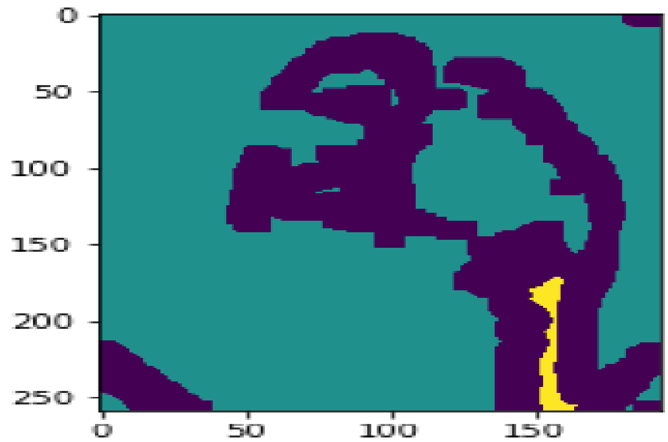
Until teaching them, the MLP and SVM enable the extraction of specific features to be added to the classifiers. In this article, using a histogram-based approach, the ROI of DM patients is segmented prior to feature extraction. A variety of image segmentation methods have been developed in the process of obtaining the partition of a digital image into several segments, such as thresholding, clustering-based methods, compression-based methods, histogram-based methods, and edge detection, among others. This work uses a method based on a histogram, primarily using fuzzy logic, which represents the image fragments. For image processing, the fuzzy logic approach helps one to use affiliation functionality to identify the degree to which a pixel belongs to one section or another. In addition, by using fuzzy logic according to the entropy calculation, we get a clearer description of segments. The optimised parameters are derived using a heuristic optimization strategy based on Differential Evolution.



(a)



(b)



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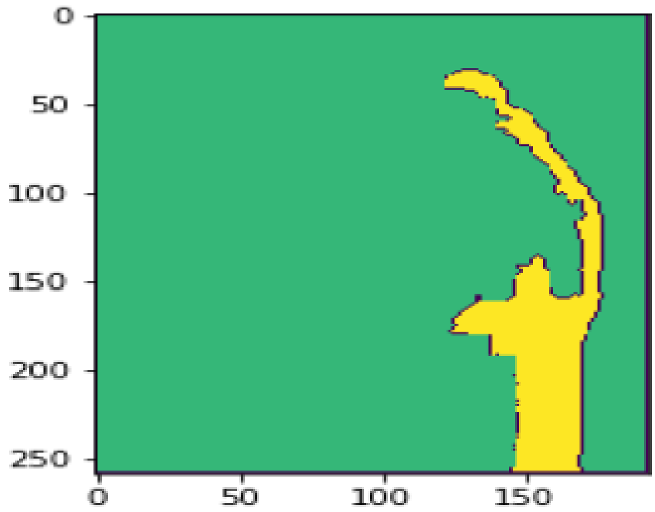


(d)

Fig 3: Step by Step Segmentation for hyper spectral image (a) Outer Layer Segmentation I, (a) Outer Layer Segmentation II, (c) Outer Layer Segmentation III, (d) Outer Layer Segmentation IV.

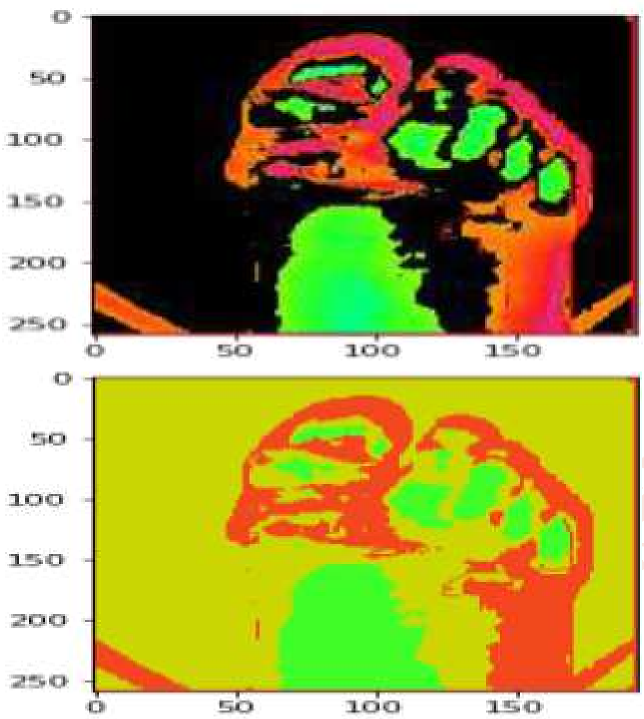


Fig 4: Step by Step Segmentation for hyper spectral image (a) Inner Layer Segmentation I, (a) Inner Layer Segmentation II.

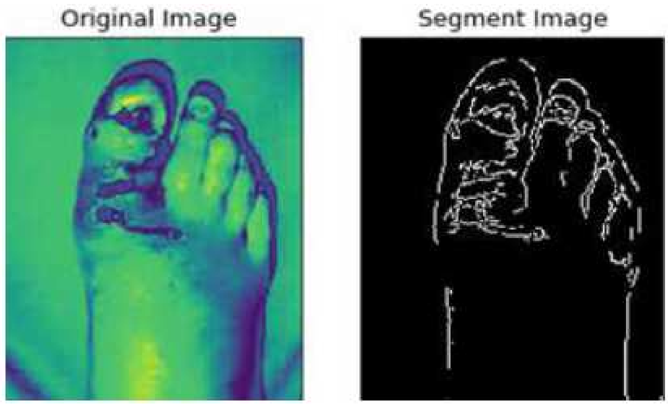


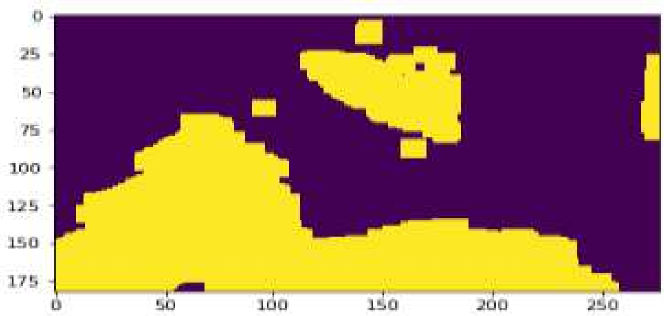
Fig 5: Segmentation Image

Machine Learning Classifiers

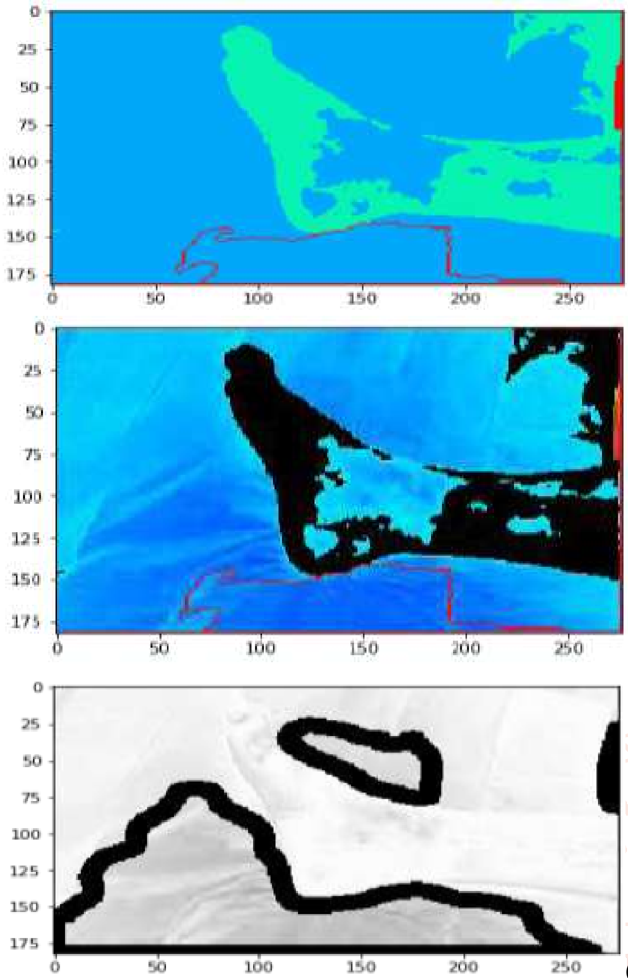
In image-based medical decision-making procedures, such as identification and diagnosis, automatic segmentation, automated image annotation, and image recovery, computer aids have become an essential requirement [54]. The use of algorithms for computational intelligence aims to address such limitations, including the exhaustive challenge of interpreting a vast number of images. Other algorithms include achieving more precise diagnostic systems, thereby offering a higher degree of efficiency that is needed by the patient. New computational algorithms according to the characteristics of the images and the high volume of data handled are needed to advance medical imaging technology, which offer new imaging modalities and methodologies. The kNN and CNN algorithms are some of the most commonly used. However, as a result of the high precision rate obtained from its dynamic learning structure and, in many situations, the large volume of data processed, DL has been used in the classification of medical images, as well as in other areas, enabling this structure to achieve several levels of feature abstractions from the data. The former two algorithms are contrasted with DL in this work, presenting the benefits and drawbacks of their use.

Multiple Classes

Previous analysis by some authors in this review has shown that local plantar temperatures can be measured based on the principle of angiosomes[19]. An angiosome is a hybrid unit of tissue supplied by an artery that provides useful temperature data related to damage to the artery. The foot is broken into four angiosomes for this purpose: the medial plantar artery (MPA), the lateral plantar artery (LPA), the medial calcaneal artery (MCA), and the lateral calcaneal artery (LCA). The knowledge collected using angiosomes is not only related to the damage caused by DM in the arteries, but also to the associated likelihood of ulceration, as it is used to measure local temperatures.



(a)



(b)

(c)

(d)

Fig 6: Multi class Clustering Techniques for hyper spectral image (a) Identify affected Area, (a) Scan angled Area, (c) Inner and outer Layer Capture image. (d) Post Processing Image

V. Experimental Results

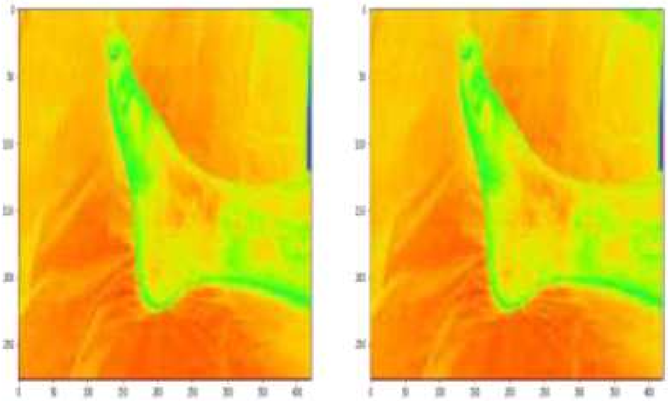
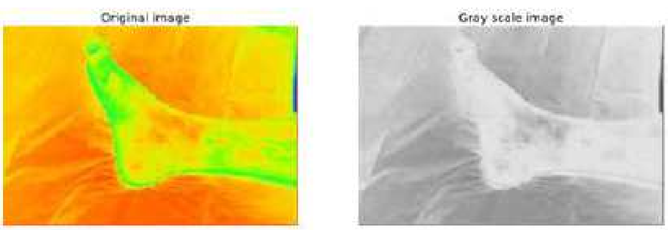


Fig 7: Original Image



(a) (b)

Fig 8: (a) Dataset Original Image, (b) Greyscale Image

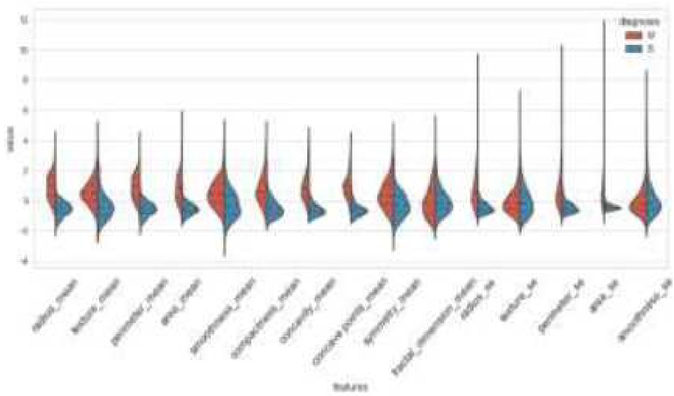


Fig 9: Hyper spectral Image metrics

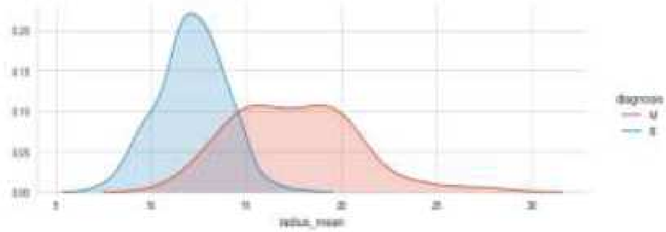


Fig 10.Radius Mean value

Table 2: Classification Report:

	Precision	Recall	F1-Score	Support
Affected	0.97	0.99	0.98	95
Non Affected	0.98	0.94	0.96	51
Accuracy			0.97	146
Macro avg	0.97	0.97	0.97	146
Weightedavg	0.97	0.97	0.97	146

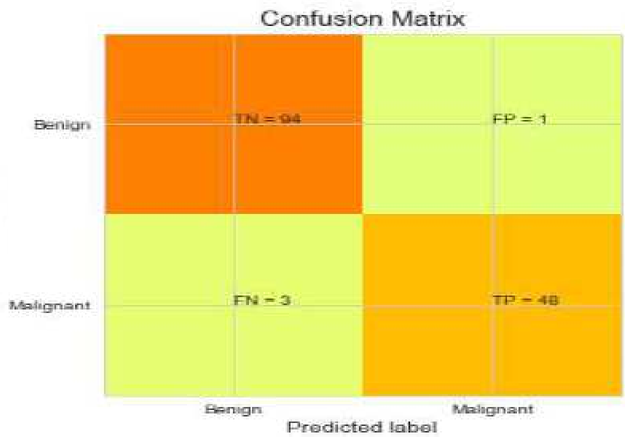


Fig 11: Confusion Matrix

VI. Conclusion:

In case of increase incidence of DM, and as a result of its most common microvascular complication, DN, the importance of understanding its main clinical signs, the current methods of investigation and the proposed therapies for early diagnosis with the potential of avoiding the progression of the disease and its complications must be emphasised. A contrast of traditional classifiers such as kNN and those of present relevance such as CNNs is provided in this work. The goal is to distinguish variations in patients with DM in hyperspectral images. The work involves the definition of five DM-patient levels. Following a function extraction method, the results of the first simulations using conventional CNN and kNN classifiers produced satisfactory results. The propensity to use DL constructs, however, is not only to improve the precision of the classification, but also, in certain situations, to prevent the exhaustive task of extracting features and segmenting the desired patterns. The use of pre-trained networks is one benefit of promoting our work in the use of those DL systems. The outcomes reached with DL are higher and have less preparation time. In the results, we can note that consecutive groups were influenced by correlations in the hyperspectral images' temperature distributions. We suggested a new version of CNN with a basic structure but a better design. The proposed architecture uses sensitivity, precision, accuracy and AUC-values tests, among others, to achieve acceptable performance, even in the worst cases of classification. With less intervention of the professional in the collection of patches and ROIs, we hope to achieve improved classification outcomes. This thesis is aimed at classifying hyperspectral images and forecasting the presence of foot ulceration. Another expansion of this work may be to identify feet with ulcerations that, as opposed to regular healthy skin, contain very distinctive texture and color characteristics.

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