Boosting Ensemble Performance and Subspace Analysis Diabetes Foot Ulcer Classification using Integrated Gradients Convolution Learning Model

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Abstract: Aging and diabetes lead to protein glycation and cause dysfunction of collagen-containing tissues. The accompanying structural and functional changes of collagen significantly contribute to the development of various pathological malformations affecting the skin blood vessels and nerves causing a number of complications increasing disability risks and threat to life. In fact no methods of non-invasive assessment of glycation and associated metabolic processes in bio tissues or prediction of possible skin complications e.g. ulcers currently exist for endocrinologists and clinical diagnosis. In this publication utilizing emerging photonics-based technology innovative solutions in machine learning and definitive physiological characteristics we introduce a diagnostic approach capable of evaluating the skin complications of diabetes mellitus at the very earlier stage. Dermatology is one of the most unpredictable and difficult terrains to diagnose due to its complexity. In the field of dermatology extensive tests are to be carried out to decide upon the skin condition the patient may be facing. The time may vary from practitioner to practitioner. This is also based on the experience of that person too. So, there is a need of a system which can diagnose the skin diseases without any of these constraints. We propose an automated image-based system for recognition of skin diseases using machine learning classification. Many skin diseases have highly similar visual characteristics which add more challenges to the selection of useful features from the image. The accurate analysis of such diseases from the image would improve the diagnosis, accelerates the diagnostic time and leads to better and cost-effective treatment for patients. This existing system will utilize computational techniques to analyze process and relegate the image data predicated on various features of the images. Skin images are filtered to remove unwanted noise and process it for enhancement of the image. Feature extraction using complex techniques such as Convolutional Neural Network (CNN) classify the image based on the algorithm of softmax classifier and obtain the diagnosis report as an output. In this paper an automatic facial skin defects detection and recognition system is proposed. The system automatic locates the facial region and extracts the region of interest. A ResNet-based classifier is then used to classify the potential defects into spot acne and normal skin. In this research we have tried to develop a prototype to detect skin diseases using neural networks. In the choice of neural networks we have chosen ResNet which is a convolutional neural network.

Keywords: Artificial intelligence, biomedical imaging, computational and artificial intelligence, diabetes, machine learning, medical diagnostic imaging

INTRODUCTION

The Diabetic Foot Ulcer (DFU) is one of the major complications resulting from diabetes which can lead to lower limb amputation. Regular foot check by clinical professionals is required for patients with DFU development which is often costly and / or requires referral to specialist care. Research shows that healthcare services that treat DFU are unable to handle the growing number of patients due to inadequately trained medical staff which is especially prevalent in low-income countries and rural areas. The prevention is better than cure principle applies aptly in diabetic foot ulcer (DFU) and can be achieved by motivating patients towards self-monitoring. People involved in self-management can help prevent/postpone the appearance of an ulcer by detecting the corresponding signs and symptoms early on. Additionally monitoring of existing ulcers is advised to prevent complications or re- current ulceration. During DFU monitoring there are various signs and symptoms that should be taken under consideration including: skin color change (redness) skin temperature change foot pressure induced injury (damage to the skin and/or underlying soft tissue) pain swelling or odor. Today most of these DFU indication signs can be captured and consequently monitored using various optical sensors such as those integrated in mobile devices . It is intriguing the fact that RGB and thermal sensors can support DFU monitoring. Some major advantages of these types of sensors involve the relatively low acquisition costs compact structure and easy integration to portable devices. Typically, the raw data provided by the sensors are fed to complex AI tools which serve as decision making mechanisms. There are multiple studies advocating that AI tools coupled with optical sensors can provide extremely useful decision support mechanisms. Such mechanisms can assist both physicians and patients to prevent undesirable situations. Treatment for DFU can be a long-term process due to diabetes-related complications impairing the healing process. It requires a multi-disciplinary team to monitor the progress of the ulcer focusing largely on the management of diabetes and blood flow to the foot. However, complications such as infection significantly prolong treatment. If treatment is prolonged the possibility of infection and amputation increases significantly. This has been shown to create a heavy burden on healthcare systems in terms of both time and cost per patient. Furthermore, this causes a great deal of concern due to the predicted rapid global rise of diabetes amplified significantly by the current pandemic. To address these challenges researchers have been working towards development of methods and automated systems capable of detecting and monitoring DFU. Improvements to automated delineation of DFU could support improved digital healthcare tools that could be used for screening and triage of DFU. Furthermore, these improvements could aid in the development of active DFU monitoring systems to engage the healing process stage. The estimated number of diabetes mellitus cases was 463 million (9.3% of the global population) in 2019, and it is predicted to increase to 578 million cases (10.2%) by 2030. Diabetic foot syndrome, a long-term complication that can cause neuropathy and ischaemia, is associated with this disease. If not properly monitored and cared for, diabetic foot ulcers (DFUs) may develop, which have a global prevalence of 6.3% in diabetics. Impaired wound healing and complications like infections can lead to chronicity, making regular screening and documentation necessary. Inadequate care can prolong treatment, exacerbate the problem, and ultimately result in amputations, which have a significant impact on quality of life and are susceptible to complications. Machine learning-based applications can assist overwhelmed caregivers and promote best practices by automating time-consuming tasks and offering decision support at the point-of-care. These include the early detection of adverse shifts in wound healing progress such as infection and ischaemia. The DFU Challenge (DFUC) is a series of academic challenges that focus on tasks related to DFU care, allowing for a broad comparison of detection, classification, and segmentation methods and an evaluation of potential applications' state of the art.

MOTIVATION

Diabetic foot ulcers (DFU) are one of the most serious complications that can result from diabetes and often lead to amputation of all or part of a limb if not met with timely treatment. Early detection of DFU together with accurate screening for infection and ischemia can help in early treatment and avoidance of further serious complications including amputation. This motivates us.

OBJECTIVES

I. To investigate the effect of image processing refined contours on the performance of a popular deep learning algorithm.

II. To provide an in-depth analysis on the performance of baseline results.

III. To ensure smoothing process does not alter the clinical delineation.

IV. To be able to slow down the attenuation of errors in each hidden layer, ensuring the stability of gradient weight information

V. To proceed the global average pooling layer which is connected using a parallel structure.

PROBLEM STATEMENT

In DFU assessment using deep learning methods include:

- High inter-class similarity and intra-class variations of the infection and ischemia wound classes in DFU images.
- Highly variable and non-standardized DFU dataset imaging conditions with large variations in the camera's distance from the foot its orientation (pose) and lighting conditions.
- Lack of patient demographic information such as patient ethnicity age sex foot size or any accompanying meta-data for the DFU.

LITERATURE SURVEY

The paper "Robust Methods for Real-Time Diabetic Foot Ulcer Detection and Localization on Mobile Devices" [1] deals with current practice for diabetic foot ulcers (DFU) screening that involves detection and localization by podiatrists. Existing automated solutions focus on either segmentation or classification, but the proposed method combines both aspects for more accurate localization. The authors collected a dataset of 1775 DFU images, and two medical experts annotated the regions of interest. The dataset was then used to train a deep learning model using five-fold cross-validation. The authors achieved a mean average precision of 91.8% using faster R-CNN with InceptionV2 model using two-tier transfer learning. The model had a speed of 48 ms for inferencing a single image and a model size of 57.2 MB. To demonstrate the practicality of the proposed method, the authors evaluated the performance of the models on a NVIDIA Jetson TX2 and a smartphone app. The results show that the deep learning model can be used for real-time prediction of DFU localization. The authors suggest that the proposed method can be further improved with a larger and more diverse dataset. This work showcases the potential of deep learning methods in improving the accuracy and speed of DFU screening and can potentially reduce the need for podiatrists in the screening process.

"Plantar Thermogram Database for the Study of Diabetic Foot Complications" [2] investigates the advances in infrared thermography during recent years have opened new possibilities for its use in medical diagnosis. This paper discusses the use of infrared thermography for the early diagnosis of complications related to diabetic foot and introduces a new public plantar thermogram database which includes 334 plantar thermograms from 122 diabetic subjects and 45 non-diabetic subjects. Each thermogram includes four extra images with their respective temperature file, corresponding to the four plantar angiosomes. The paper explains the plantar thermogram acquisition protocol, including the acquisition system and the proper preparation of the subject. It also provides a brief review of the techniques used in previous works for segmentation, registration, and correction of feet posture. The database is expected to provide a valuable source for researchers to explore the potential of infrared thermography for the early diagnosis of diabetic foot problems.

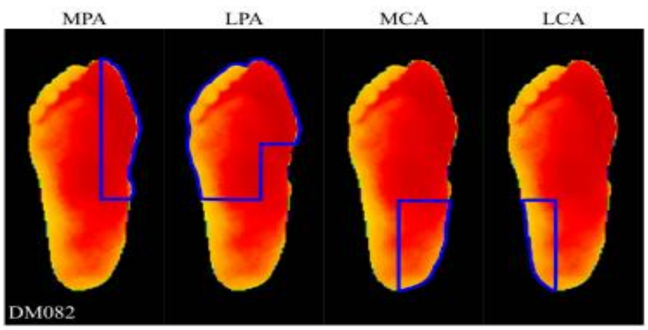


Fig 1: Plots corresponding to 4 angiosomes

Next, we look into the paper "An Integrated Design for Classification and Localization of Diabetic Foot Ulcer Based on CNN and YOLOv2-DFU Models" [3]. Diabetes is a chronic disease that can lead to complications such as diabetic foot ulcers (DFU) if not treated in time. DFU can be classified into two categories: infection (bacteria) and ischaemia (inadequate blood supply). Detecting DFU in the initial phase is difficult, and this research proposes a 16-layer convolutional neural network (CNN) for classification and YOLOv2-DFU for localization of infection/ischaemia models. Deep features are extracted and supplied to several classifiers for analysis, and it was found that DT and softmax achieved consistent results for the detection of ischaemia/infection. The proposed method was validated on the newly developed DFU-Part (B) dataset and compared with the latest published work using the same dataset. Grad-Cam model is used to visualize the high-level features of the infected region for better understanding, and the Shuffle network is utilized as the mainstay of the YOLOv2 model for infected region localization. The proposed method provides a non-invasive and efficient way to detect DFU, which can help clinicians find potential diabetic foot patients earlier and prevent foot amputations.

"Automatic Diabetic Foot Prediction Through Fundus Images by Radiomics Features" [4]. Current approaches to treating diabetic foot (DF) rely heavily on clinician vigilance and laboratory tests, which have limitations such as high costs and demanding professional skills. Existing research on DF prediction mainly uses regression analysis of clinical data and recognition based on foot ulcers skin. To address this, we propose using fundus images to develop a new and efficient method for DF prediction. In this study, we introduce a DF prediction model that uses radiomics features extracted from fundus images. We extract twelve types of radiomics features, including information on image texture, direction, phase, and gradient, that have previously been applied in the field of medical imaging. We then use a two-step feature selection model to identify the best combination of features. After considering both model simplicity and performance, we selected 19 features to train the support vector machine model. To evaluate the performance of the model, we conduct 5-fold cross-validation on clinical data. The model achieves an impressive mean prediction performance with an area under the curve of 0.9678, sensitivity of 0.9786, specificity of 0.9161, and accuracy of 0.9247. Our findings demonstrate the effectiveness of our DF prediction model and suggest it could be an essential tool for clinicians to detect potential diabetic foot patients earlier, providing a new noninvasive and efficient method for early DF prediction.

"Laser Speckle Integrated Multispectral Imaging System for In-Vivo Assessment of Diabetic Foot Ulcer Healing: A Clinical Study" [5]. The study highlights the growing concern regarding the high prevalence of diabetes mellitus and diabetic foot ulcer (DFU) worldwide. The paper presents a diagnostic tool that aims to predict tissue oxygen saturation (StO2) and blood perfusion levels in the affected limb using imaging techniques. The tool uses multispectral imaging and laser speckle contrast imaging to map tissue oxygen and blood perfusion levels in the ulcerated foot. The study found that high tissue oxygenation and perfusion levels are critical to ensuring progressive wound healing in DFU patients. A longitudinal study revealed that there was a slightly higher mean StO2 and blood perfusion level in healed ulcers than in impaired healing. However, the data indicated no statistical significance between these two groups ($p\text{-value} > 0.05$). The study observed that a mean StO2 of at least 70% and blood perfusion value of 1.5 (103) are necessary during the proliferative phase to ensure progressive healing. Based on these findings, the study concludes that high tissue oxygenation and perfusion levels are crucial to ensure progressive wound healing in DFU patients. The diagnostic tool developed in this study can provide a rationale for evaluating the healing outcomes of skin grafting procedures in diabetic ulcers by observing quantitative changes in blood perfusion and tissue oxygen level during the revascularization phase.

"Machine Learning in the Prevention, Diagnosis and Management of Diabetic Foot Ulcers: A Systematic Review" [6]. This paper investigates Diabetic foot ulcers (DFUs) and how they are a serious complication for people with diabetes, often leading to increased morbidity and significant pressures on healthcare resources. The emergence of machine learning (ML) technology presents an opportunity to improve care for people at risk of DFUs by identifying and synthesizing evidence about the current uses and accuracy of ML in the interventional care and management of DFUs. This, in turn, can provide a reference for future research and highlight areas where further study is needed. To investigate the use of ML in DFUs, the researchers conducted a systematic review of literature using the Preferred Reporting Items for a Systematic Review and Meta-analysis of Diagnostic Test Accuracy Studies (PRISMA-DTA) guidelines. They searched databases including PubMed, Google Scholar, Web of Science, and Scopus for papers mentioning ML and DFUs and reporting relevant outcome measures regarding ML algorithm accuracy. They used the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool to assess bias in the included studies. Of the 3,769 papers reviewed, 37 were deemed eligible based on the selection criteria. The papers reported on the accuracy of multiple types of ML algorithms used in DFU studies, with all studies reporting at least 90% accuracy compared to gold standards using a minimum of one ML algorithm for processing or recording data. These algorithms showed positive effects on DFU data analysis and outcomes, particularly in image segmentation and classification, raw data analysis, and risk assessment. However, the current research in this area is still limited, and future studies should address areas such as direct comparisons of ML applications with current standards of care, health economic analyses, and large-scale data collection. Although ML has the potential to offer an effective and accurate solution to guide data analysis and procurement from DFU interventions in small samples and study conditions, there is currently not enough evidence to confidently suggest that ML methods in DFU diagnosis are ready for implementation and use in healthcare settings.

“Statistical Approximation of Plantar Temperature Distribution on Diabetic Subjects Based on Beta Mixture Model” [7]. This paper discusses the use of infrared thermography to detect tissue damage, inflammation, or peripheral vascular abnormalities associated with diabetic foot by analyzing changes in the distribution of plantar temperature. However, there are challenges in detecting abnormalities on each foot separately. To address this issue, the authors propose a probabilistic approach to characterize the plantar temperature distribution. The goal is to detect temperature variations on each foot without comparing it to the opposite foot. The authors used a beta mixture model with four components to approximate the plantar temperature distributions of both diabetic and non-diabetic subjects. Each component represents a specific area of the plantar region, such as the toes, metatarsal heads, arch, and heel. The approach was tested on 60 temperature distributions of non-diabetic subjects and 220 of diabetic subjects. The results suggest that the distribution can be characterized based on the mean of its beta components. This approach can potentially improve the detection of abnormalities associated with diabetic foot and help with early intervention.

” Diabetic Sensorimotor Polyneuropathy Severity Classification Using Adaptive Neuro Fuzzy Inference System” [8]. The study focused on developing an intelligent classifier for Diabetic Sensorimotor Polyneuropathy (DSPN), which is an early indicator for non-healing diabetic wounds and foot ulcers. These complications are common in diabetic patients and can lead to serious health issues such as infections, amputations, and even death. The proposed classifier used an Adaptive Neuro Fuzzy Inference System (ANFIS) and Michigan Neuropathy Screening Instrumentation (MNSI) as input to identify and stratify DSPN severity into four classes: Absent, Mild, Moderate, and Severe. The accuracy, sensitivity, and specificity of the ANFIS model were validated and showed promising results. The study also investigated changes in muscle activity during gait from three different lower limb muscles (vastus lateralis, tibialis anterior, and gastrocnemius medialis) electromyography (EMG) of DSPN patients with different severity levels classified by the proposed classifier. The results showed that VL and GM muscles demonstrated changes in activation peak delay and magnitude during gait with the progression of DSPN severity. Overall, the proposed ANFIS-based severity classifier using both MNSI variables and EMG features could help health professionals diagnose and stratify DSPN severity based on both signs and symptoms and electrophysiological changes due to DSPN. This could lead to earlier detection and timely intervention, which could potentially reduce the prevalence of DSPN complications in diabetic patients.

Next, we referenced the paper “Plantar or Palmar Tactile Augmentation Improves Lateral Postural Balance with Significant Influence from Cognitive Load” [9]. The purpose of this study was to examine how to improve postural regulation when plantar cutaneous feedback, which is the sensation of touch on the sole of the foot, is reduced. Some methods try to compensate for the reduced feedback by using other sensory cues, such as touch from another part of the body. However, this approach may not be as effective because it requires more cognitive effort to interpret these cues. The researchers wanted to test whether directly enhancing plantar cutaneous feedback would be more effective than providing compensatory sensory cues. To do this, they conducted experiments with six healthy subjects who were asked to maintain their balance on a lateral balance board. The subjects were instructed to close their eyes to rely more on plantar cutaneous feedback, and a foam pad was added to the board to simulate reduced feedback. The researchers applied electrical stimulation to either the calcaneal nerve in the foot or the ulnar nerve in the palm to enhance the sensory feedback. They also tested the effects of these interventions with and without a counting task to measure cognitive load. The results showed that plantar cutaneous augmentation was effective at improving balance only when the task included a cognitive load. In contrast, palmar cutaneous augmentation was effective only when the task did not include a cognitive load. This suggests that the location of sensory augmentation should be selected based on the attentional demands of the task.

The paper “A Sensor Gauze with Multi-Channel Moisture and pH Monitoring for Chronic Wound Care” [10] investigates chronic wounds (CWs) that usually happen in diabetic foot ulcers, venous leg ulcers, and pressure ulcers. When wounds fail to achieve sufficient healing within four weeks, it indicates that bacteria in the wounds are promoting chronicity through relapse infections. Therefore, how to observe changes in a wound after it is covered with gauze to avoid the formation of CWs is important for clinical care. Previous studies showed that wound pH value distribution can be used as an important basis for infection and healing assessment. This paper proposed the design of sensor gauze with multi-channel moisture and pH monitoring for CWs. The moisture sensing analysis of different areas could be used to determine the distribution of the corresponding wound tissue fluid, as well as automatically carry out multi-area pH value measurements and wound analysis. The analysis results were graphically displayed on a monitoring device. The results indicated that the proposed design could measure pH values with high sensitivity (0.01 pH/mV) in the range of 3 to 10. Statistical correlation analysis revealed a strong correlation (R2 = 0.97) between the standard meter and each pH sensing point. In the experimental correlation between the proposed device and the moisture device, the results show that there was a high correlation (R2 = 0.97). The response time of the whole wound scan with four channels was within one second. This design has the potential to aid with related clinical care applications.

EXISTING SYSTEM

Diabetes mellitus (DM) is a metabolic disorder characterized by increased blood glucose. Pathology can manifest itself with different conditions including neuropathy the main consequence of diabetic disease. Statistics show worrying figures worldwide diagnosed an estimated 1.6 million people with DM by . In this sense alternative and automated methods are necessary to detect DM allowing it to take the pertinent measures in its treatment and avoid critical complications such as the diabetic foot. On the other hand, foot thermography is a promising tool that allows visualization of thermal patterns that are altered as a consequence of shear and friction associated with lower limb neuropathy. Based on these considerations we explored different strategies to detect patients with DM from foot thermography in this research. Initially the study focused on forming a classification index like Thermal Change Index (TCI). Subsequently we used the deep convolutional neural networks paradigm implementing different data augmentation methods of which four are conventional and are newly proposed methods. The results showed that the proposed and the conventional methods increased the networks performance where a % detection was achieved by weighting the DM probability percentages for both images of the feet. Finally, it was also possible to demonstrate the importance of transfer learning which does not depend on the type of database but on the data corpus with which the transfer was trained. A framework for exploring different approaches for screening subjects with diabetes mellitus (DM) was proposed. Initially we planned to study a new discrimination coefficient of the subjects based on the characteristics of average temperature age overall TCI of right and left feet. The new coefficient was able to exceed the accuracy of the TCI by up to % which is a useful tool for the stratification of subjects with DM. Secondly the ResNetv network was explored to accurately classify subjects by integrating it with data augmentation methods to make up for the low corpus of thermographic image data. The augmentation consisted of conventional methods and eight proposed methods based on dimension reduction methods: principal component analysis kernel PCA incremental PCA factor analysis independent component analysis non-negative matrix factorization dictionary learning and LDA. Initially the images were taken to latent spaces of lower dimensionality using the aforementioned methods. The latent variables were altered with a random noise vector and returned to the original image space generating new synthetic images with characteristics like the reference images. All methods were shown to be statistically significant with a significance level below which is a relevant contribution to data enhancement. Additionally, a comparative analysis was performed we studied the behavior of the network under three training conditions. First the network was trained from scratch. Secondly, we used transfer learning from the conventional ImageNet image database and we performed the same process but from a thermographic database. The results showed that data augmentation and learning transfer are statistically significant strategies to improve the performance of convolutional neural networks. Furthermore, it was also shown that learning transfer has the same impact regardless of the nature of the images as long as the data corpus is large enough to generate transferable learning patterns. A. Anaya-Isaza M. Zequera-Diaz: Detection of DM With Deep Learning and Data Augmentation Techniques data in the model trained with the thermographic database. accuracy (acc) and loss scores.

EXISTING SYSTEM ISSUES

- Not capable of detecting co-occurrence of infection and ischemia.
- The dataset was small and cannot be generalized.
- The dataset was highly imbalanced, with infection cases significantly outnumbering ischemic case
- This system is Opportunistic and uncontrollable.
- Narrowly specialized knowledge
- Have not been investigated thoroughly.
- May take huge time and economic cost to construct.

DATASET DESCRIPTION

Dataset URL: https://ieee-dataport.org/open-access/plantar-thermogram-database-study-diabetic-foot-complications

Dataset Description: The database presented comprises thermograms of the plantar region, collected from both diabetic (DM group) and non-diabetic individuals (control group). The significance of this database lies in the investigation of temperature distribution in the plantar region of both groups and the measurement of their differences. Past literature reports indicate that increased plantar temperature is linked to a higher risk of ulceration. Thus, examining how thermal changes occur in the plantar region and how they can be quantified is critical for developing new diagnostic support tools that aid medical professionals in taking preventive measures. The thermogram database was obtained from diabetic and non-diabetic subjects, and additional details on the analysis of thermograms for diabetic foot complications can be found in the corresponding author's scientific reports

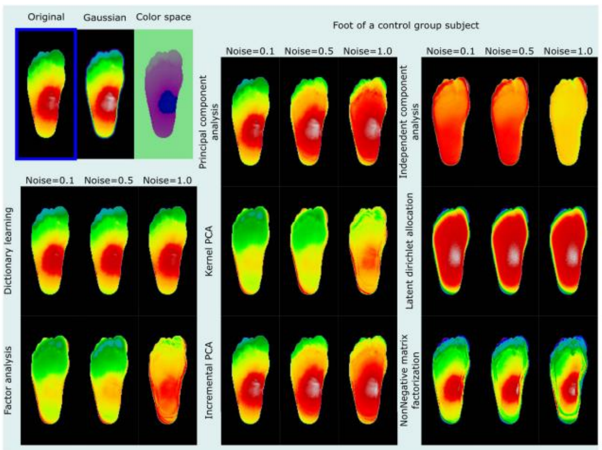


Fig 2: Thermal Images (Thermograms)

PROPOSED ARCHITECTURE

In this proposed work we constructed a database composed initially of various facial skin images belonging to different people. We have taken the images from Dermnet. We have considered skin infection pictures with the natural parts. It has been seen that the proposed framework yield exactness differs as for skin illnesses. We have additionally gathered pictures from the web. More pictures have been downloaded on various unique infections. The image is standardized in this phase by removing noise like hair and skin pigments as it can confuse the analysis. Also, the image which is given as the input maybe not be of standard size as required by the algorithm, so it is necessary that required image size is obtained. In the beginning the images are regenerated using some preprocessing image techniques to augment the size of our database collected from different sources and resized to fit the network. These images are then used for training and validation purposes. We will show that our model can successfully identify eight facial skin diseases. Facial skin diseases identification and classification is done by a pretrained ResNet network model. Its architecture is mainly formed of three types of layers: convolutional layer pooling layer and fully connected layer. The input image passes through a series of convolution layers with filters to extract the features. Then a non-linear activation function is applied. The most used function is Rectified Linear Unit (ReLU) because it fastens the training phase. The obtained feature maps pass through pooling layers to reduce their dimensionality size and hence control overfitting. Max or average pooling could be performed. The output obtained is flattened and then fed into the fully connected layer. Finally, the images are classified using a Softmax activation function.

ADVANTAGES OF PROPOSED SYSTEM

- Works with a very high degree of confidence.
- Better operational efficiency.
- Tolerates Variations.
- Increased efficiency and speed.
- Minimizes the workload on infrastructures.
- Quick and efficient to use.

HARDWARE & SOFTWARE REQIREMENTS

Hardware Requirements:

- Processor: Minimum i3 Dual Core.
- Ethernet connection (LAN) OR a wireless adapter (Wi-Fi).
- Hard Drive: Minimum 100 GB; Recommended 200 GB or more.
- Memory (RAM): Minimum 8 GB; Recommended 32 GB or above.

Software Requirements:

- Python
- Anaconda
- Jupyter Notebook
- TensorFlow
- Keras

ALGORITHMS

Existing Algorithm:
Latent Dirichlet Allocation
Proposed Algorithm:
Integrated Gradients Convolution Learning Model

ADVANTAGES OF PROPOSED ALGORITHM

Integrated Gradients Convolution Learning Model Algorithm Advantages:

- It tries to learn the difference between the learned features and if the learned feature is not useful in the final decision weights become zero for the particular feature.
- Gives higher accuracy especially for classification problem.
- Accelerate the speed of training.

MODULES

Module 1: Data Visualization and Understanding

Data Visualization and Understanding is all about getting to know and understand your data before making any assumptions about it or taking any steps in the direction of Data Mining. It helps you avoid creating inaccurate models or building accurate models on the wrong data. We used frequency distribution tables bar charts histograms or pie charts for the graphical representation in Univariate visualizations.

Module 2: Data Pre-processing

A real-world data generally contains noises missing values and maybe in an unusable format which cannot be directly used for machine learning models. Data preprocessing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model. Most of the datasets are incomplete inconsistent inaccurate (contains errors or outliers) and often lacks specific attribute values/trends. This is where data preprocessing enters the scenario. It helps to clean format and organize the raw data thereby making it ready-to-go for Machine Learning models.

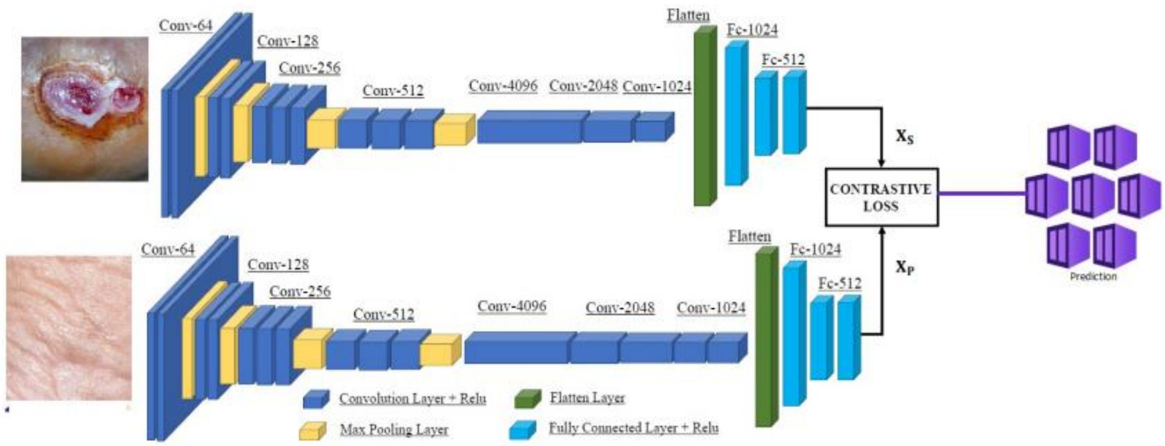


Fig. 3: Proposed Architecture Diagram

Fig 4: Dataset Image Sharpening

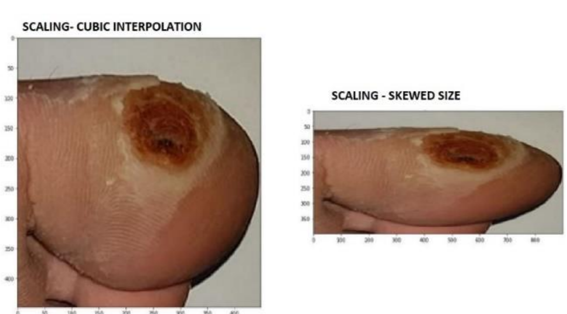
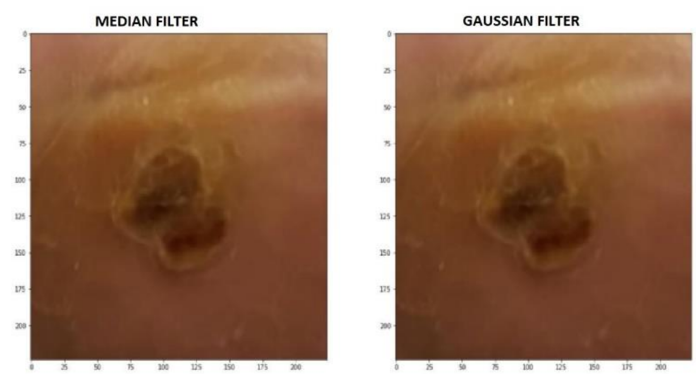
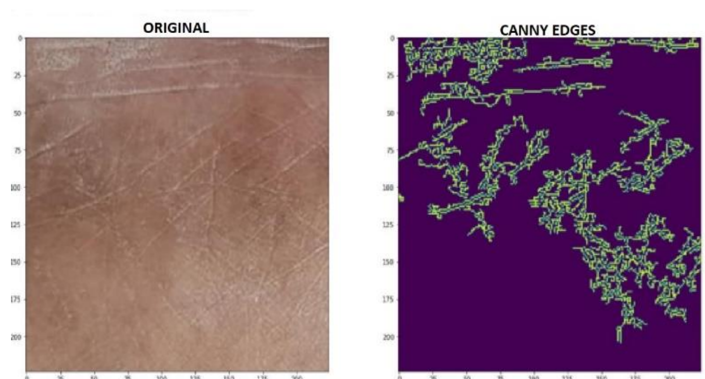


Fig 5: Scaling (Cubic Interpolation and Skewed Size)

Fig 6: Median & Gaussian Filter Applied





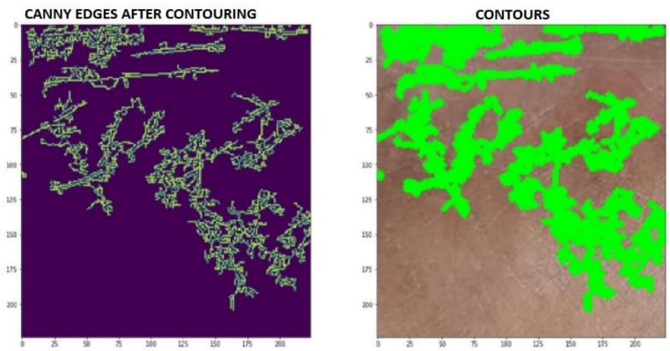
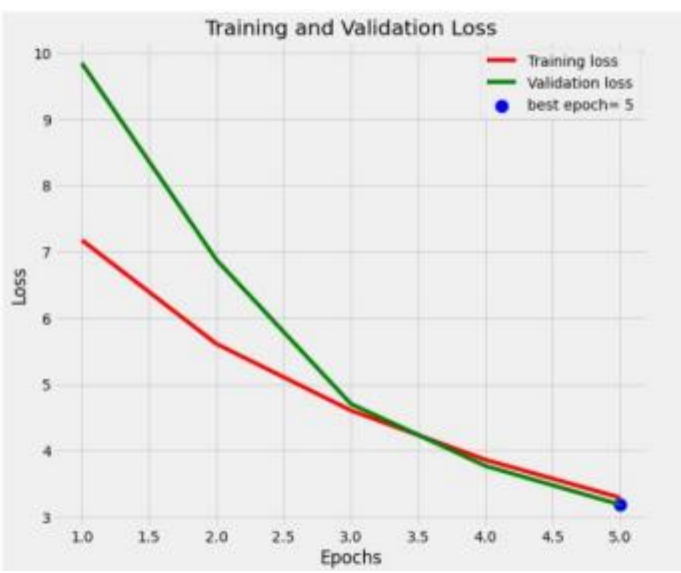


Fig 7: Canny Edges Contouring (Before/After)

Module 3: Train the Model

Creating a train and test split of your dataset is one method to quickly evaluate the performance of an algorithm on your problem. The training dataset is used to prepare a model to train it. We pretend the test dataset is new data where the output values are withheld from the algorithm. We gather predictions from the trained model on the inputs from the test dataset and compare them to the withheld output values of the test set. Comparing the predictions and withheld outputs on the test dataset allows us to compute a performance measure for the model on the test dataset. This is an estimate of the skill of the algorithm trained on the problem when making predictions on unseen data. A final machine learning model is a model that you use to make predictions on new data. To train a model we need access to the data several utility functions and we need multiple iterations / passes through the dataset. The training process will effectively use both functions repeatedly: Initially the parameters of the model are randomly instantiated. Next the score of the model is checked. If the score is deemed insufficient (often because it has improved compared to the previous iteration) the model parameters are updated and the process is repeated.



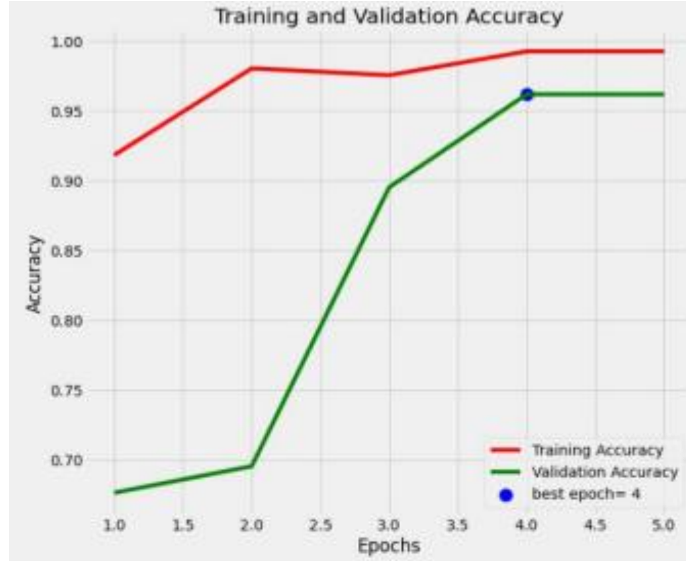


Fig 8: Base Model Training & Validation Loss and Accuracy

CONCLUSION AND FUTURE WORK

Conclusion:

We intend to refresh this framework for the usage of the task all things considered. In this paper a new automated facial skin diseases diagnosis method based on machine learning approach is presented. The prediction of diseases is achieved by a pretrained Convolutional Neural Network. We used ResNet model. The model was trained and validated by a database that we have created containing various images. It achieves the highest possible accuracy and classifies successfully the facial skin images given for test with an high accuracy. This is done with the help of the different operations of the ResNet such as Convolution Max Poolingetc till the image flattens out into a image vector. These are the vectors with which classification can be done as these vectors contain the information leading to the determination of high-level features.

Future work:

Technical advances help expand the applicability to different skin diseases. For example, the finding of arborizing vessels can be a useful clue for early diagnosis of basal cell carcinoma and a finer blood vasculature detection can enhance the diagnosis accuracy between actinic keratosis and basal cell carcinoma.

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