ISSN: 2320-2882

IJCRT.ORG



INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

DETECTION OF DIABETES MELLITUS WITH DEEP LEARNING AND DATA AUGMENTATION TECHNIQUES ON FOOT THERMOGRAPHY

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Abstract: Diabetes mellitus is a metabolic condition characterized by persistently elevated blood glucose levels (DM). Hyperglycemia, the medical term for abnormally high blood glucose levels, is a hallmark of diabetes mellitus. Diabetes mellitus (DM) develops from a combination of hereditary and environmental factors that lead to immune system dysfunction and insulin resistance. Factors that increase the likelihood that you may get diabetes include having a high body mass index or having a first-degree relative who has the disease (BMI) The global prevalence of obesity has risen as a result of poor dietary practices and an increase in sugar intake. Statistics all throughout the globe are showing the effects. The global prevalence of diabetes is increasing, with an estimated 1.6 million people having the disease by the year 2025. Diabetic microvascular problems, such as diabetic foot, may be prevented with early diagnosis and appropriate treatment, hence voluntary and automated procedures for detecting DM are crucial. Alternatively, foot thermography is a potential technology because it enables viewing of thermal patterns, patterns that are changed due to shear and friction associated with lower limb neuropathy. For the purpose of synthesizing thermal images of the foot, we use the usage of categorization indices such as the Thermal Change Index (TCI). In light of these considerations, in this investigation we use deep convolutional neural networks, using 12 distinct data augmentation approaches, to identify DM patients based on foot thermography alone.

Index Terms - Deep Learning, Diabetic Foot Ulcer(DFU), Thermography, AlexNet, KNN, DefNet,

I. INTRODUCTION

About 463 million persons had diabetes in 2019, according to data from the International Diabetes Federation compiled by Saeedi et al. It is predicted that by 2045, this figure would have increased to 700 million.[1][2] A diabetic individual has a 34% chance of getting a foot ulcer at some point in their lives (DFU). Or, put another way, 1 in 3 diabetics will eventually be diagnosed with a DFU. When Armstrong et al (2017)[3]. DFU infection. causes substantial morbidity, psychological suffering, and shortened life expectancy due to the amputation of affected limbs. The findings from this study will form the basis of an ongoing initiative to improve the treatment of diabetic feet. Clinicians presently do this vital periodic monitoring of foot ulcers manually in order to determine the healing of the ulcer[4][5]. In order to better remember the course of ulcers over time, several foot clinics now photograph them during both the first examination and the future evaluations. Common complications of diabetes mellitus (DM) include cardiovascular disease, stroke, renal failure, blindness, ischemia, and peripheral vascular disease[6]. The most prominent form of neuropathic change, the diabetic foot, is caused by peripheral vascular disease. Reduced mobility is a result of the condition, which causes infections, ulcers, or profound tissue degeneration in the lower leg.

The goal of the present investigation is to create deep learning algorithms based on AI that can identify ulcers without the need for human involvement. At a time when social distance is of utmost relevance due to the prevalence of COVID, this is of critical importance. Improving ulcer diagnosis and treatment regimens using technology may be a game-changer for the treatment of diabetic feet. Detection tasks may be more difficult in real-world contexts because to the abundance of potentially confounding ambient factors.

Some examples of these kind of observations include, Care providers may overlook recently gained and unobtrusive beginning phases of ulceration during visual examination of previously acquired problems owing to the limited period allowed for routine treatment. Because of time requirements during treatment and documentation, in any event, when led by talented individuals, many injury photographs experience the ill effects of unfortunate concentration, movement obscure, impediment, unfortunate enlightenment, and backdrop illumination.

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False positive detections, such as those caused by twisted toenails, profound rhagades, collapsed removal scars, and new epithelialization, might be amended physically, but this can be tedious when recording DFU[7][8]. Typical wound care paperwork often includes details on ulcers that are both extremely little and very big and curved, both of which might cause problems for particular detectors. Creating a technology answer that can revolutionize present screening techniques is crucial because it has the potential to drastically lessen clinical time constraints.

Thanks to the rapid development of deep learning, automated analysis of DFU is now a realistic possibility. However, in order for deep learning to provide results on par with those of human experts, massive datasets are required. The bulk of medical imaging studies conducted at present cannot be repeated because their authors operate in silos[9][10]. Yap et al. (2020c,b) suggested the diabetic foot ulcer challenges in order to close the knowledge gap and encourage data exchange between researchers and doctors. This paper gives an outline of the present status of-the-craftsmanship computational techniques for DFU recognition, portrays the freely accessible datasets, assesses famous item identification systems for DFU discovery, recommends an outfit approach and Outpouring Consideration DetNet for DFU location, and tests profound learning calculations on the DFUC2020 dataset.

Studies using thermography of the face or tongue to diagnose type 2 diabetes are also under underway. In this article, we introduce thermography as a revolutionary technique for investigating various states; such pictures have seen substantial development in ongoing many years attributable to their painless nature, and are presently even used in face identification.

Because of their digital nature, thermographic pictures may also be incorporated into other AI approaches. A number of studies are currently underway to aid in the diagnosis of DM and the early identification of related problems including neuropathy and diabetic foot ulcers, so progress has not been slow in arriving.

II LITERATURE SURVEY

We reviewed the following previous papers and projects on diabetic ulcer detection for our project.

Thirunavukkarasu et al Implemented foot thermography and also utilised the technique on detection of diabetes type 2 is from the facial or tounge thermography in 2020. Thermography offers a fresh approach to diagnosing a wide variety of symptoms. Those photos are also utilized in facial recognition, and they've seen significant increase in the last decade thanks to their noninvasive nature. In addition, the digital representations of temperature differences in thermographic pictures allows for unification with a variety of AI strategies.

D. Martin, Bayareh and Sruthi et al. Several research studies have focused on the diagnosis of DM or identifing symptoms that are in squelae, such as neurological complications or diabetic foot growing interest has also spured low-cost implement proprietary to enter such thermographic images. In other hand ,approached from the subject covering topics from various film processing for state of the art deep learning networks.

Asymmetric analysis between angiosomes is proposed as a means of identifying individual differences by Christy Evangeline and colleagues, as well as by David R. Martin and Charles C. Martin. The new coefficient, such as the Thermal Change Index, was proposed by Filipe et al (TCI). The clustering technique is performed to the image's quantifiable levels, and the foot is then divided into sections (temperature). From these regional temperature estimates, a threshold coefficient for temperature categorization may be derived (CTT).

In order to facilitate feature extraction in images, such as photographs, F. Pedro, Prabhu, and colleagues developed an autonomous technique to segment the plantar foot area of thermographic images. The C++ algorithm has been created for this purpose.

To Adam and the rest of us.

Similarly, the classification system relies on a support vector machine.

Deteriorated from the Discrete Wavelet Change (DWT) and the Higher-request range, the model utilizes the Dim Level Co-event Network (GCLM), Hu's invariant second (HIM), nearby twofold example (LBP), misfortune surface energy (LTE), and entropy. The creator brought up that the work depended on a more modest data set and that feature extraction was necessary for the system's partial automation. In their paper, the authors provide figures that are greater than those found in prior studies.

In order to aid physicians' visual recall, many foot clinics now routinely photograph ulcers at both the initial assessment and review phases.

Coronary illness, stroke, renal disappointment, visual deficiency, ischemia, and fringe vascular sickness are just not many of the significant intricacies of diabetes mellitus. The most noticeable form of neuropathic change, the diabetic foot, is caused by peripheral vascular disease. Patients with this condition often find themselves unable to move about freely due to infections, ulcers, or the breakdown of deep tissue in the lower leg.

This study's overarching goal is to create deep learning systems powered by AI that can identify ulcers in the absence of human involvement. In the contemporary COVID context, when social distance is of utmost significance, this is of critical relevance. Developing better ulcer diagnosis and treatment approaches might be a game changer for the treatment of diabetic feet. Detection tasks may be difficult when considering the wide variety of factors present in real-world environments.

Just a few examples of things that have been noticed include, Because of the restricted time assigned for routine treatment, recently obtained and unpretentious beginning phases of ulceration are frequently ignored via care staff during visual assessment. Because of restricted time for treatment and documentation, in any event, when directed by talented individuals, bad quality photographs with frail concentration, movement obscure, impediment, unfortunate lighting, and backdrop illumination are run of the mill in injury documentation.

False positive detections, such as those caused by malformed toenails, deep rhagades, folded amputation scars, and new epithelialization, need manual correction, which may be time intensive when recording DFU. Some detectors have trouble with extremely tiny, very big, or curved ulcers, however these descriptions are prevalent in wound care literature. In order to dramatically lessen clinical time pressures, it is crucial to provide a technical solution capable of modifying present screening processes.

Automatic DFU analysis is already a reality because to the rapid development of deep learning systems. However, in order to produce findings on par with those of human experts, deep learning needs massive datasets. Most medical imaging studies cannot be repeated since researchers do them individually at present.

The experiment by Nag et al. First-order statistical features are obtained using GLCM-based textures and features based on wavelets, following five preceding processes of classification, acquisition, data preparation, analysis, measurements, and feature insertion. In the end, they use three different machine learning techniques to accomplish classification: support vector machine (SVM), kNN, and decision tree (DT), with DT achieving the highest accuracy at 97.78 percent.

A research based on the acquisition of standing thermographs is conducted by Thirunavukkarasu et al., which goes against the grain of earlier advancements. Accuracy of over 81% is achieved by SVM as toe, metatarsal 1, 3, 5, instep, and heel temperatures are measured. Vardasca et al. categorize the diabetic foot using dynamic thermography. The suggested research relied on three different machine learning methods and a total of 12 temperature landmarks to differentiate between study subjects. Incorporating the kNN algorithm into the development allowed for an 81% success rate.

To conclude, Cruz-Vega et al. use a deep learning paradigm artificial neural network and support vector machine. After some preliminary analysis, we receive a number of traits that we then use in the development phase. They also include the AlexNet deep learning network with the raw data, leading to superior cross-validation classification results. A similar convolutional neural network to AlexNet, dubbed DFTNet, was presented by Cruz-Vega et al. a year later. What's more, the multi-facet perceptron and support vector machine are examined. Exactness near 95% is accomplished when the main model is prepared utilizing the crude information and the second and third models are prepared with highlights got from the areas of interest. As well, Khandakar et al. offer a dual-pronged approach to identifying diabetic foot problems. The first one makes use of standard machine learning techniques, while the second one derives from detection using various deep learning networks. ISSUE 10 59565, 2022 The Diabetic Microbiome: Detection by A. Anaya-Isaza and M. Zequera-Diaz Accuracy of almost 96 percent was achieved using deep learning and data augmentation techniques to tailor the analysis to each individual participant.

III MATERIALS AND METHODS

A.DATASET

The dataset containing images of the diabetic foot ulcers and normal foot images with the classification i.e. normal are to be classified is split into training and testing dataset with the test size 30-20%.

B.DATA PREPROCESSING:After converting the. csv lines to the'float32'format, we now get single-channel photos. Image dimensions were forced to be 19988, and those that fell short were bottom-padded to make up the difference. The photos were then normalized relative to the maximum and lowest values in the dataset; for example, temperatures between 15.98 and 37.28 degrees Celsius were assigned numerical values between 0 and 1.



Figure 1. Diabetic foot with the plots corresponding to the 4 angisomes

C. CONVOLUTIONAL NEURAL NETWORK

One of the many-faceted computational sciences subfields is man-made reasoning. Man-made intelligence incorporates anything from the most fundamental straight model frameworks to the most recent profound learning methods. One of the foundations of simulated intelligence are convolutional counterfeit brain organizations, frequently known as convolutional networks. One sort of naturally roused framework depends on the construction and activity of the cerebrum, or the focal sensory system all the more explicitly.

They can do more and more difficult jobs because of the complexity and variety of their structures. There are two negative aspects to the deeper exploration. To begin, a bigger number of layers and, by extension, training parameters is implied by a higher depth.

Because of this, fitting multiple model parameters requires a much larger amount of training data. This is one reason why we decide to utilize information expansion methods and consolidate creative ways to deal with this issue. Second, the model preparation created by slope blurring is obliged by the expansion of convolutional layers.

That's why we choose to utilize the Mobilenet network in this study—it includes a clever workaround for that problem. The network is predicated on the idea of residual mapping, or connections between nodes. The link often establishes parallel routes to the convolutional layer arrangements, working with the inclination's smooth transmission through the layers and keeps the slope esteem from becoming invalid. Besides, the organization is constrained into learning the remaining planning f (x)x, which is less difficult to prepare assuming that the leftover planning is the personality capability f (x) = x [50], [67].

Layers used to build ConvNets

A covnets is a hierarchical network where each layer maps one volume to another using a differentiable functions. As an example, let's apply covnets to a 32-by-32-by-3-pixel picture. Types of Layers:

1. Input Layer: This layer contains the picture's crude info, which has the accompanying aspects: 32 pixels wide by 32 pixels high by 3 pieces inside and out.

2. Convolution Layer: The second layer, called the convolution layer, is responsible for calculating the final volume of the picture by taking the spot result of the channels in general and picture patches. On the off chance that we use 12 channels in this layer, the resulting volume will be 32 by 32 by 12.

3. Activation Function Layer: The third layer, called the activation function layer, takes the results from the convolution layer and applies an activation function to each individual element. RELU: max(0, x), Sigmoid: 1/(1+e-x), Tanh, Leaky RELU, etc., are all examples of popular activation functions. Due to the fact that the volume hasn't changed, the output volume will be 32 by 32 by 12.

4. Pool Layer: a Pool Layer is used in covnets to minimize overfitting, decrease computation time, lower memory requirements, and increase accuracy. Maximum pooling and average pooling layers are two of the most popular kinds of pooling layers. With a maximum pool, two-by-two filters, and a stride of two, the resulting volume is 16 by 16 by 12. D.MOBILENET

To filter pictures, mobile net is a model that, like CNN, uses convolution. However, it does so in a manner that is distinct from traditional CNN.

The Convolutional Neural Network (CNN) architecture Mobile Net is efficient and portable, making it useful in practical settings. To create more lightweight models, mobile nets predominantly employ profundity wise divisible convolutions as opposed to the ordinary convolutions utilized in past plans. Because of the expansion of two new worldwide hyper boundaries (width multiplier and goal multiplier), model makers may now optimize MobileNets for latency, accuracy, speed, or size, as needed.



Figure2. MobileNet representation

1.Standard Convolution Layer

As seen in the table above, a single convolution unit (denoted Conv) looks like this:



Figure3. Standard Convolution Layer

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2.Depth wise separable Convolution layer Above, we have a table depicting a single Depth-wise separable convolution unit designated by the symbol Conv dw.:



Figure4.Depthwise seperable Layer 3.Width Multiplier

The width multiplier (denoted by) is a global hyperparameter that helps build compact and efficient models for computation. Its numerical value ranges from 0 to 1. This reduces the computational cost and model size at the expense of performance for a given layer and value of, where M is the quantity of information channels and N is the quantity of result channels. Reduced by a factor of nearly 2, both the calculation cost and the number of parameters are much more manageable. Common examples of values are 1, 0.75, 0.5, and 0.25.

4.Resolution Multiplier

Resolution multiplier (or simply) is MobileNets' second new parameter. Lower the input image's resolution using this hyperparameter, which will also reduce the input to each layer by the same amount. Input picture resolution is 224 * for a fixed value of. The computational cost is cut in half as a result.

E.PRINCIPAL COMPONENT ANALYSIS

One way to reduce the number of dimensions in a data collection is to utilize principal component analysis (PCA), which reduces the number of latent variables involved. This technique uses linear combination of the data to generate new variables. These sub-parts are created in a hierarchical structure, with each sub-level keeping some of the original data's unpredictability. The largest share of variability goes towards producing component z1, with successive components using progressively decreasing shares. As seen in Eq. (1) or (2), the first PC may be written as a dot product.

 $z_1 = u_1 1x_1 + u_1 2x_2 + u_1 3x_3 + \ldots + u_1 mxm (1)$ $z_1 = U_1 \cdot X (2)$

F.KERNEL PCA

For use with nonlinear data, principal component analysis (PCA) was expanded into the kernel PCA. The informational collection is projected onto a higher layered include space utilizing a capability implemented via kernel principal component analysis. In other words, the dimensionality of the original data set is decreased using the PCA approach by first projecting it onto a higher dimensional space that can be partitioned linearly. For example, the Gaussian filter (Equation 1) is only one kind of filter that may be employed with this approach. (3).

$x_3 = e - x_1 - \mu_1 \sigma_{12} + x_2 - \mu_2 \sigma_2$ (3)

G. INCREMENTAL PCA

Incremental PCA is another modification of traditional PCA that is used when the original PCA is too inefficient to handle the data set size. Free of how much information tests, the methodology utilizes a low-rank guess for the information.

I.FACTOR ANALYSIS

The technique of factor analysis, which involves the projection of a collection of variables onto a space of reduced dimensionality called "factors," is one of the most widely used techniques of multivariate analysis for investigating the connection between such sets of data. The factor analysis paradigm implies that the original p variables may be explained by a set of m common factors (m p) plus a single component. This may be written mathematically using Eqs. (4) and (5).

 $x1 = u11f1 + u12f2 + u13f3 + \ldots + u1mfm + \varepsilon 1 x2 = u21f1 + u22f2 + u23f3 + \ldots + u2mfm + \varepsilon 2 \ldots xp = up1f1 + up2f2 + up3f3 + \ldots + upmfm + \varepsilon p (4)$

X = UF + E (5) where X is the vector of the first factors ($X \in R p$), U is the component network or grid with factor loadings ($U \in R p \times m$), F is the vector of normal variables ($F \in R m$), and E is the vector of one of a kind elements ($E \in R p$).

J. INDEPENDENT COMPONENT ANALYSIS

Free part examination is a famous strategy utilized in measurements to recognize a direct portrayal of non-Gaussian information where the parts of the new portrayal are measurably autonomous. It is feasible to gauge the free parts as a straight blend of the first factors, as displayed in Condition (7) or (8), for an informational index addressed with m factors (X R m).

s1 = w11x1 + w12x2 + w13x3 + ... + w1mxm s2 = w21x1 + w22x2 + w23x3 + ... + w2mxm ... sm = wm1x1 + wm2x2 + wm3x3 + ... + wmmxm (6)

 $\mathbf{S} = \mathbf{W} \cdot \mathbf{X} (7)$

From this starting point, the matrix W, which is estimated by maximizing W's non-Gaussianity, determines the components or latent variables. K. NON-NEGATIVE MATRIX FACTORIZATION

Non-negative framework factorization, frequently called non-negative grid estimate, is a dimensionality decrease strategy that approximates two matrices by factoring the observations of the matrix X. To simplify inspection of the final matrices, the approach uses the assumption that the three matrices are all positive-definite. According to Equation (which demonstrates the mathematical definition of the observations matrix), the observations matrix is an approximate representation of two matrices. (8).

 $X \approx WH(8)$

The goal function is written as an equation, and it is used in the estimate of the two new matrices (9).

For this purpose, the WH matrices are computed such that the goal function approaches 59569 at volume 10. M. Zequera-Diaz, and A. Anaya-Isaza: Detection of DM With Deep Learning and Data Augmentation Techniques its smallest possible value [77], [78]. $OF = 1.2 \text{ kX} - \text{WHk } 2 + \alpha \text{wL1m kWk1} + \ldots + \alpha \text{hL1n kHk1} + \ldots + 1.2 \alpha \text{w} (1 - \text{L1}) \text{ m kWk } 2 \text{ F} + \ldots + 1.2 \alpha \text{m} (1 - \text{L1}) \text{ m kWk } 2 \text{ F}$

Here, w and h denote the respective matrices' regularization coefficients. The Frobenius standard, otherwise called the Hibert-Schmidt standard, is characterized as follows: where L1 is the regularization blending boundary, m is the quantity of factors or elements in the first set, n is the quantity of tests or perceptions, kk1 is the l1 standard, and k.kF is the Frobenius standard (10). kAkF = Xm j=1 Xn k=1 aj,k2 1 2 (10)here, aj,k is each of the elements of the m × n-dimensional matrix A.

IV EXPERIMENTAL DESIGN

The Kruskal-Wallis test statistic was first used to examine the individuals' characteristics. Temperature (general and angiosomal), TCI coefficient, age, and sex were among the parameters that were compared between the control group (CG) and diabetes mellitus (DM). To better distinguish between the individuals, a new coefficient was developed using the results of this validation. The temperature histogram was additionally explored, yielding normal bends and mistake groups for the two gatherings and each foot. Thermographic pictures were then captured and processed in accordance with the procedures outlined in the methodology. We downsized the photos to 199 88, normalized them, split them up into training and test data sets, and then used 5-fold cross-validation to assess their quality.

We took the photos from the training data as a baseline and used the methods of:

- Vertical flipping
- Flip vertically.
- Shift in color space.
- Gaussian linear filtering
- Analysis of the principal components
- PCA for the kernel.
- PCA with increments.
- Analysis of factors.
- Analysis of independent components.
- Factorization using a non-negative matrix
- Learning about dictionaries.

A technique known as latent dirichlet allocation. A convolutional neural network, ResNet50v2, was trained using the enhanced pictures and a variety of various parameters. The first training was done from scratch, which means that random values were used to set the training parameters. Two, the organization was instructed utilizing move gaining with loads extricated from the ImageNet information base. In the latter, weights created during MobileNet training were utilised during the transfer. An appendix displays the outcomes of this program. The network was then tested on the test set and scored based on several metrics like accuracy, sensitivity, specificity, F1 score, and precision after it had been trained.

The organization was likewise prepared multiple times each crease with the accompanying hyperparameters:

Fifty epochs have passed.

Loss function: cross-entropy

Adadelta, the Optimizer

Uniform Glorot or Transfer Learning for weight initialization, if necessary.

Zeros or Transfer Learning for Bias Initialization.

• The maximum number of items in a batch is 16. Python was used to model the architecture, namely the Keras and TensorFlow frameworks.



Figure5.Block Diagram of Diabetic Foot Detection

V RESULT

Training without using any data augmentation strategies yielded encouraging and statistically meaningful outcomes. Additionally, the same procedures were employed to increase the size of the preexisting dataset. The neural network was trained using synthetic versions of the reference images; this method ensured perfect correctness. It should be made clear, however, that there are limits to the study. It has not been confirmed if these correlate to the degree of severity of the disease, but first, the new coefficient provides a stratification of the individuals that corresponds to their nature (see Figure 7). And there's no clinical evidence to back up these numbers, so additional research is needed to confirm their accuracy. Second, the study could only use data from one central location, which is likely not diverse enough for the purpose of the inquiry. Some research topics are also left open by this experimental design, which might be investigated in further studies. Without taking into account the fact that each approach was applied independently, the methods enabled us to achieve this remarkable level of performance. As a result, it would be helpful to investigate if the combination of the approaches would result in higher performance, or to ask whether there may be a mix of ways that enhances the performance of convolutional networks. Last but not least, while MOBILENET exhibited good results, it contains many training parameters; hence, it would be interesting to evaluate whether the suggested approaches have the same influence on lowerorder network structures. Classifies the output and determines the ulcer in the foot.



Diabetic Ulcer

Figure6. Classified Output Result

VI CONCLUSION AND FUTURE ENHANCEMENT

It was suggested to use a framework to investigate various methods of diabetic mellitus (DM) screening. Initially, we intended to investigate a novel subject discriminating coefficient based on average temperature, age, and total TCI of right and left foot. The new coefficient is an effective tool for stratifying people with DM, with an accuracy that may be up to 17% higher than that of the TCI.

After combining the mobile network with 12 data augmentation techniques to compensate for the small dataset of thermographic images, we found that it could be used for accurate subject classification. Principal component analysis (PCA), kernel PCA (KPCA), incremental PCA (Incremental PCA), factor analysis (FA), independent component analysis (ICA), non-negative matrix factorization (NMF), dictionary learning (DL), and latent dirichlet allocation (LDA) were the eight dimension reduction techniques used to augment the original four methods. These techniques were first used to transport the pictures to lower dimensions latent spaces. Reference pictures were used to generate new synthetic images with similar features, after which the latent variables were perturbed

using a random noise vector and then restored to the original image space. All of the approaches were found to be statistically significant at a p value of less than 0.05, making a valuable addition to the field of data augmentation.

In spite of its potential usefulness in preventing and treating diabetic foot disease, thermal imaging is not yet routinely used in clinical practice. The scope of use for infrared imaging has broadened thanks to technological developments.

The reason for this study was to move toward researching the practicality of involving high-goal infrared warm imaging for the robotized, painless ID of side effects of diabetic foot illness.

An algorithm built on collection and analysis parameters from a high-resolution infrared camera and a computer may identify diabetic foot disease and differentiate between the absence of illness, localized disease, and widespread disease. This is a major step toward the development of a smart telemedicine monitoring system for the automatic, noninvasive identification of diabetic foot illness. More research is needed to validate and expand upon these preliminary results. At present, the analysia is limited to detecting the diabetic region in the foor based on the image provided by the user. It can be further enhanced to detect the type of ulcer and stage of the disease.

The future scope for the project are:

- Detection of Type of Diabetes whether it is timely or lifetime.
- Stage of the disease and analysis of the region that might spread the disease.
- Differentiate the ulcers in the foot.
- Accuracy of the disease along with remedy.

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