A Deep Learning Approach to Universal Skin Disease Classification

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Abstract: Lot of skin diseases are common nowadays because of different infection to body. Proposed work will demonstrate the classification of skin diseases using proposed implementation using MATLAB. Matlab is one of the leading software which helps us to design and analyze proposed system for skin disease classification. We used deep learning algorithm for skin disease classification which is based on autoencoders. Two level autoencoder shows better performance compared to the existing state of art techniques. Proposed system is analyzed by both subjective and objective analysis and proved that proposed work performs better in case of huge dataset also

Index Terms: skin diseases, deep learning, image classification, auto encoders.

INTRODUCTION

Skin diseases are one of the most commonly seen infections among people. Due to the disfigurement and associated hardships, skin disorders cause lots of trouble to the sufferers [13]. Speaking of skin cancer, the facts and figures become more serious. In United States, skin cancer is the most common form of cancer. According to a 2012 statistics study, over 5.4 million cases of no melanoma skin cancer, including basal cell carcinoma and squamous cell carcinoma, are treated among more than 3.3 million people in America [20]. In each year, the number of new cases of skin cancer is more than the number of the new incidence of cancers of the breast, prostate, lung and colon in combined [24]. Research also shows that in the course of a lifetime, one-fifth of Americans will develop a skin cancer [19].

However, the diagnosis of skin disease is challenging. To diagnose a skin disease, a variety of visual clues may be used such as the individual lesional morphology, the body site distribution, color, scaling and arrangement of lesions. When the individual components are analyzed separately, the recognition process can be quite complex [6, 15]. For example, the well-studied skin cancer, melanoma, has four major clinical diagnosis methods: ABCD rules, pattern analysis, Menzies method and 7-Point Checklist. To use these methods and achieve a good diagnostic accuracy, a high level of expertise is required as the differentiation of skin lesions need a great deal of experience. Unlike the diagnosis by human experts which depends a lot on subjective judgment and is hardly reproducible, a computer aided diagnostic system is more objective and reliable.

By using well-crafted feature extraction algorithms and combining with some popular classifiers (e.g. SVM and ANN), current state of art computer aided diagnostic systems can achieve very good performance on certain skin cancers such as melanoma. But they are unable to perform diagnosis over broader classes of skin diseases. Human engineered feature extraction is not suitable for an universal skin disease classification system. On one hand, hand-crafted features are usually dedicated for one or limited number of skin diseases. They can hardly be applied to other classes and datasets. One the other hand, due to the diversity nature of skin diseases [6], human engineering for every skin disease is unrealistic.

One way to solve this problem is to use feature learning [4] which elim- inates the need for feature engineering and lets the machine to decide which feature to use. Many feature learning based classification systems have been proposed in past few years . However, they have been mostly restricted to dermoscopy or histopathology images. And they mainly focus on the detection of mitosis, an indicator of cancer. In recent years, deep convolutional neural networks (CNN) become very popular in feature learning and ob- ject classification. The use of high performance GPU makes it possible to train a network on a large-scale dataset so as to yield a better performance.

II. LIST OF SKIN CONDITIONS

Many conditions affect the human integumentary system the organ system covering the entire surface of the body and composed of skin, hair, nails, and related muscle and glands. The major function of this system is as a barrier against the external environment. The skin weighs an average of four kilograms, covers an area of two square meters, and is made of three distinct layers: the epidermis, dermis, and subcutaneous tissue. The two main types of human skin are: glabrous skin, the hairless skin on the palms and soles (also referred to as the "palmoplantar" surfaces), and hair-bearing skin. Within the latter type, the hairs occur in structures called pilosebaceous units, each with hair follicle, sebaceous gland, and associated arrectorpili muscle. In the embryo, the epidermis, hair, and glands form from the ectoderm, which is chemically influenced by the underlying mesoderm that forms the dermis and subcutaneous tissues.

The epidermis is the most superficial layer of skin, a squamous epithelium with several strata: the stratum corneum, stratum lucidum, stratum granulosum, stratum spinosum, and stratum basale. Nourishment is provided to these layers by diffusion from the dermis, since the epidermis is without direct blood supply. The epidermis contains four cell types: keratinocytes, melanocytes, Langerhans cells, and Merkel cells. Of these, keratinocytes are the major component, constituting roughly 95 percent of the epidermis. This stratified squamous epithelium is maintained by cell division within the stratum basale, in which differentiating cells slowly displace outwards through the stratum spinosum to the stratum corneum, where cells are continually shed from the surface. In normal skin, the rate of production equals the rate of loss; about two weeks are needed for a cell to migrate from the basal cell layer to the top of the granular cell layer, and an additional two weeks to cross the stratum corneum.

The dermis is the layer of skin between the epidermis and subcutaneous tissue, and comprises two sections, the papillary dermis and the reticular dermis. The superficial papillary dermis interdigitates with the overlying rete ridges of the epidermis, between which the two layers interact through the basement membrane zone. Structural components of the dermis are collagen, elastic fibers, and ground substance. Within these components are the pilosebaceous units, arrectorpili muscles, and the eccrine and apocrine glands. The dermis contains two vascular networks that run parallel to the skin surface one superficial and one deep plexus which are connected by vertical communicating vessels. The function of blood vessels within the dermis is fourfold: to supply nutrition, to regulate temperature, to modulate inflammation, and to participate in wound healing.

The subcutaneous tissue is a layer of fat between the dermis and underlying fascia. This tissue may be further divided into two components, the actual fatty layer, or panniculusadiposus, and a deeper vestigial layer of muscle, the panniculuscarnosus. The main cellular component of this tissue is the adipocyte, or fat cell. The structure of this tissue is composed of septal (i.e. linear strands) and lobular compartments, which differ in microscopic appearance. Functionally, the subcutaneous fat insulates the body, absorbs trauma, and serves as a reserve energy source. Conditions of the human integumentary system constitute a broad spectrum of diseases, also known as dermatoses, as well as many nonpathologic states (like, in certain circumstances, melanonychia and racquet nails). While only a small number of skin diseases account for most visits to the physician, thousands of skin conditions have been described.

Classification of these conditions often presents many nosological challenges, since underlying etiologies and pathogenetics are often not known. Therefore, most current textbooks present a classification based on location (for example, conditions of the mucous membrane), morphology (chronic blistering conditions), etiology (skin conditions resulting from physical factors), and so on. Clinically, the diagnosis of any particular skin condition is made by gathering pertinent information regarding the presenting skin lesion(s), including the location (such as arms, head, legs), symptoms (pruritus, pain), duration (acute or chronic), arrangement (solitary, generalized, annular, linear), morphology (macules, papules, vesicles), and color (red, blue, brown, black, white, yellow). Diagnosis of many conditions often also requires a skin biopsy which yields histologic information that can be correlated with the clinical presentation and any laboratory data.

III. OVERVIEWOF SKIN

Human skin, except for palms and soles, is quite thin and of variable thickness. It has two layers: the epidermis (outer) and dermis (inner). Collagen and elastic components in the dermis allow it to function as a flexible barrier. The skin provides a unique shield which protects within limits against mechanical forces, or penetration by various chemical agents. The skin limits water loss from the body and guards against the effects of natural and artificial light, heat and cold. Intact skin and its secretions provide a fairly effective defence zone against micro-organisms, providing mechanical or chemical injury does not impair this defence. Provides an illustration of the skin and description of its physiological functions.

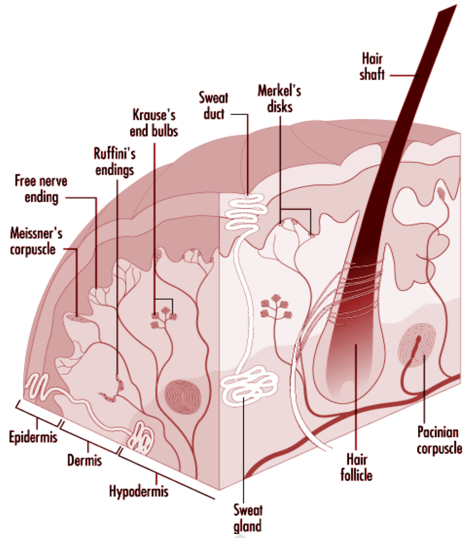

Figure 1.1 Schematic representation of the skin

The outer epidermal layer of dead cells (keratin) provides a shield against elements in the outside world. These cells, if exposed to frictional pressures, can form a protective callus and can thicken after ultraviolet exposure. Keratin cells are normally arranged in 15 or 16 shingle-like layers and provide a barrier, though limited, against water, water-soluble materials and mild acids. They are less able to act as a defence against repeated or prolonged contact with even low concentrations of organic or inorganic alkaline compounds. Alkaline materials soften but do not totally dissolve the keratin cells. The softening disturbs their inner structure enough to weaken cellular cohesiveness. The integrity of the keratin layer is allied to its water content which, in turn, influences its pliability. Lowered temperatures and humidity, dehydrating chemicals such as acids, alkali, strong cleaners and solvents, cause water loss from the keratin layer, which, in turn, causes the cells to curl and crack.

This weakens its ability to serve as a barrier and compromises its defence against water loss from the body and entry of various agents from outside. Cutaneous defence systems are effective only within limits. Anything which breaches one or more of the links endangers the entire defence chain. For example, percutaneous absorption is enhanced when the continuity of the skin has been altered by physical or chemical injury or by mechanical abrasion of the keratin layer. Toxic materials can be absorbed not only through the skin, but also through the hair follicules, sweat orifices and ducts. These latter routes are not as important as transepidermal absorption. A number of chemicals used in industry and in farming have caused systemic toxicity by absorption through the skin.

Some well-established examples are mercury, tetraethyllead, aromatic and amino nitro compounds and certain organophosphates and chlorinated hydrocarbon pesticides. It should be noted that for many substances, systemic toxicity generally arises through inhalation but percutaneous absorption is possible and should not be overlooked. A remarkable feature of cutaneous defence is the ability of the skin to continually replace the basal cells which provide the epidermis with its own built-in replication and repair system. The skin's ability to act as a heat exchanger is essential to life. Sweat gland function, vascular dilation and constriction under nervous control are vital to regulating body heat, as is evaporation of surface water on skin. Constriction of the blood vessels protects against cold exposures by preserving central body heat. Multiple nerve endings within the skin act as sensors for heat, cold and other excitants by relaying the presence of the stimulant to the nervous system which responds to the provoking agent.

A major deterrent against injury from ultraviolet radiation, a potentially harmful component of sunlight and some forms of artificial light is the pigment (melanin) manufactured by the melanocytes located in the basal cell layer of the epidermis. Melanin granules are picked up by the epidermal cells and serve to add protection against the rays of natural or artificial light which penetrate the skin. Additional protection, though less in degree, is furnished by the keratin cell layer which thickens following ultraviolet exposure. (As discussed below, for those whose worksites are outdoors it is essential to protect exposed skin with a sun-screen coating agent having a protective against UV-A and against UV-B (rating of 15 or greater) together with appropriate clothing to provide a high level of shielding against sun light injury.)

IV. LITERATURE SURVEY

[1] J. Arevalo, A. Cruz-Roa, V. Arias, E. Romero, and F. A. Gonzalez. An unsupervised feature learning framework for ´ basal cell carcinoma image analysis. Artificial intelligence in medicine, 2015.

The paper addresses the problem of automatic detection of basal cell carcinoma (BCC) in histopathology images. In particular, it proposes a framework to both, learn the image representation in an unsupervised way and visualize discriminative features supported by the learned model.

The proposed UFL-representation-based approach outperforms state-of-the-art methods for BCC detection. Thanks to its visual interpretation layer, the method is able to highlight discriminative tissue regions providing a better diagnosis support. Among the different UFL strategies tested, TICA-learned features exhibited the best performance thanks to its ability to capture low-level invariances, which are inherent to the nature of the problem.

[2] J. Arroyo and B. Zapirain. Automated detection of melanoma in dermoscopic images. In J. Scharcanski and M. E. Celebi, editors, Computer Vision Techniques for the Diagnosis of Skin Cancer, Series in BioEngineering, pages 139–192. Springer Berlin Heidelberg, 2014.

The incidence of malignant melanoma continues to increase worldwide. This cancer can strike at any age; it is one of the leading causes of loss of life in young persons. Since this cancer is visible on the skin, it is potentially detectable at a very early stage when it is curable. New developments have converged to make fully automatic early melanoma detection a real possibility. First, the advent of dermoscopy has enabled a dramatic boost in clinical diagnostic ability to the point that melanoma can be detected in the clinic at the very earliest stages. The global adoption of this technology has allowed accumulation of large collections of dermoscopy images of melanomas and benign lesions validated by histopathology. The development of advanced technologies in the areas of image processing and machine learning have given us the ability to allow distinction of malignant melanoma from the many benign mimics that require no biopsy.

These new technologies should allow not only earlier detection of melanoma, but also reduction of the large number of needless and costly biopsy procedures. Although some of the new systems reported for these technologies have shown promise in preliminary trials, widespread implementation must await further technical progress in accuracy and reproducibility. In this paper, we provide an overview of computerized detection of melanoma in dermoscopy images. First, we discuss the various aspects of lesion segmentation. Then, we provide a brief overview of clinical feature segmentation. Finally, we discuss the classification stage where machine learning algorithms are applied to the attributes generated from the segmented features to predict the existence of melanoma.

The early detection of melanoma is essential for successful treatment. Because dermoscopy images are so inexpensive to obtain and so widely available, they provide the most viable option for application of new image processing and machine learning algorithms. Therefore, melanoma detection using dermoscopy images has the most potential for disruption of the current clinical paradigm of waiting until the melanoma is at a later stage and performing an excessive number of biopsies. The advent of a fast, accurate and cost-effective on-the-spot technology, in the clinic or even at home, is most likely to be afforded by the type of computer analysis of dermoscopy images described here. Dermoscopy images come with various aberrations and artifacts and hence it is crucial to follow the proper steps and methods described here to remedy these abnormalities and achieve a correct diagnosis. Lesion segmentation with acceptable tolerance allows for acceptable precision in feature segmentation which in turn helps in maximizing classification accuracy. Although lesion segmentation, feature segmentation, feature generation and classification are the major steps, proper attention should be given to the auxiliary steps which in most cases are the major contributors to an exemplary outcome.

[3] C. Barata, J. Marques, and T. Mendonc¸a. Bag-of-features classification model for the diagnose of melanoma in dermoscopy images using color and texture descriptors. In M. Kameland A. Campilho, editors, Image Analysis and Recognition, volume 7950 of Lecture Notes in Computer Science, pages 547–555. Springer Berlin Heidelberg, 2013.

The identification of melanomas in dermoscopy images is still an up to date challenge. Several Computer Aided-Diagnosis Systems for the early diagnosis of melanomas have been proposed in the last two decades. This chapter presents an approach to diagnose melanomas using Bag-of-features, a classification method based on a local description of the image in small patches. Moreover, a comparison between color and texture descriptors is performed in order to assess their discriminative power. The presented results show that local descriptors allow an accurate representation of dermoscopy images and achieve good classification scores: Sensitivity = 93% and Specificity = 88%. Furthermore it shows that color descriptors perform better than texture ones in the detection of melanomas.

This chapter investigates the applicability of local color and texture features to the melanoma classification problem. Several factors associated with the performance of BoF were tested, namely the type of descriptors used and the classification algorithm. The results show that individually color descriptors perform better than texture descriptors and that good classification results can be achieved using kNN (SE = 93%, SP = 85% with $hLa{*}b{*}$ and SE = 100%, SP = 75% with $hL{*}uv$) and SVM (SE = 93%, SP = 88% with MOpp). The fusion of color and texture descriptors also achieved good results, with a score of SE = 96%, SP = 82% for the combination of Opp moments with Gabor and Laws texture descriptors. A simple analysis of the visual words showed that the dictionary obtained using BoF has potential to be used as a detector/identifier for specific dermoscopic features and patterns. Future work will rely on testing this hypothesis in order to develop a more medical oriented system. Moreover, sparse sampling methods should be tested in order to compare their performances with that of the dense sampling used in this chapter. Finally, high-level descriptors should be tested as well.

[4] Y. Bengio, A. Courville, and P. Vincent. Representation learning: A review and new perspectives. IEEE Trans. Pattern Anal. Mach. Intell., 35(8):1798–1828, Aug. 2013.

The success of machine learning algorithms generally depends on data representation, and we hypothesize that this is because different representations can entangle and hide more or less the different explanatory factors of variation behind the data. Although specific domain knowledge can be used to help design representations, learning with generic priors can also be used, and the quest for AI is motivating the design of more powerful representation-learning algorithms implementing such priors. This paper reviews recent work in the area of unsupervised feature learning and deep learning, covering advances in probabilistic models, auto-encoders, manifold learning, and deep networks. This motivates longer-term unanswered questions about the appropriate objectives for learning good representations, for computing representations (i.e., inference), and the geometrical connections between representation learning, density estimation and manifold learning.

This review of representation learning and deep learning has covered three major and apparently disconnected approaches: the probabilistic models (both the directed kind such as sparse coding and the undirected kind such as Boltzmann machines), the reconstruction-based algorithms related to auto encoders, and the geometrically motivated manifold-learning approaches. Drawing connections between these approaches is currently a very active area of research and is likely to continue to produce models and methods that take advantage of the relative strengths of each paradigm.

[5] H. Chang, Y. Zhou, A. Borowsky, K. Barner, P. Spellman, and B. Parvin. Stacked predictive sparse decomposition for classification of histology sections. International Journal of Computer Vision, 113(1):3–18, 2014.

Image-based classification of histology sections, in terms of distinct components (e.g., tumor, stroma, normal), provides a series of indices for histology composition (e.g., the percentage of each distinct components in histology sections), and enables the study of nuclear properties within each component. Furthermore, the study of these indices, constructed from each whole slide image in a large cohort, has the potential to provide predictive models of clinical outcome. For example, correlations can be established between the constructed indices and the patients' survival information at cohort level, which is a fundamental step towards personalized medicine. However, performance of the existing techniques is hindered as a result of large technical variations (e.g., variations of color/textures in tissue images due to non-standard experimental protocols) and biological heterogeneities (e.g., cell type, cell state) that are always present in a large cohort.

We propose a system that automatically learns a series of dictionary elements for representing the underlying spatial distribution using stacked predictive sparse decomposition. The learned representation is then fed into the spatial pyramid matching framework with a linear support vector machine classifier. The system has been evaluated for classification of distinct histological components for two cohorts of tumor types. Throughput has been increased by using of graphical processing unit (GPU), and evaluation indicates a superior performance results, compared with previous research.

[6] N. Cox and I. Coulson. Diagnosis of skin disease. Rook's Textbook of Dermatology, 7th edn. Oxford: Blackwell Science, 5, 2004.

The late Arthur Rook established the Textbook of Dermatology as the most comprehensive work of reference available to the dermatologist. Covering all aspects of skin disease from basic science through pathology and epidemiology to clinical practice, the text is recognized for its unparalleled coverage of diagnosis. Hailed by reviewers as 'a thorough, modern masterpiece' and 'the best textbook of dermatology in the world', and trusted by dermatologists around the world for accurate and comprehensive coverage, this clinical classic is the definitive source of information for all dermatologists. The new edition of this venerable classic extends the standard of excellence to include: All-new coverage of cosmetic dermatology and sexually transmitted diseases. More material on evidence-based dermatology. Increased coverage of dermoscopy. More emphasis on therapeutics throughout the set. More contributions from a greater variety of international experts. New page design with larger illustrations for more immediate recognition.

The 8th Edition marks the debut of the online edition of Rook's Textbook of Dermatology, allowing users the fastest possible access to the full range of knowledge on all known dermatological conditions. With fully searchable text and a fully searchable bank of more than 3,300 downloadable images, this online version puts specific information at your fingertips - when and where you need it - and is free with purchase of the four-volume set. The person-specific access code travels with you, not your computer, so you can check with Rook from any location. With the online version, you can: Search across all four volumes simultaneously. Search all images separately. Download images into presentations. Link directly to references via a range of sources. Rook's Textbook of Dermatology, in print and now online, provides a reliable, constant companion for all dermatologists.

[7] A. Cruz-Roa, A. Basavanhally, F. Gonzalez, H. Gilmore, ´ M. Feldman, S. Ganesan, N. Shih, J. Tomaszewski, and A. Madabhushi. Automatic detection of invasive ductal carcinoma in whole slide images with convolutional neural networks. In SPIE Medical Imaging, pages 904103–904103. International Society for Optics and Photonics, 2014.

This paper presents a deep learning approach for automatic detection and visual analysis of invasive ductal carcinoma (IDC) tissue regions in whole slide images (WSI) of breast cancer (BCa). Deep learning approaches are learn-from-data methods involving computational modeling of the learning process. This approach is similar to how human brain works using different interpretation levels or layers of most representative and useful features resulting into a hierarchical learned representation. These methods have been shown to outpace traditional approaches of most challenging problems in several areas such as speech recognition and object detection. Invasive breast cancer detection is a time consuming and challenging task primarily because it involves a pathologist scanning large swathes of benign regions to ultimately identify the areas of malignancy. Precise delineation of IDC in WSI is crucial to the subsequent estimation of grading tumor aggressiveness and predicting patient outcome. DL approaches are particularly adept at handling these types of problems, especially if a large number of samples are available for training, which would also ensure the generalizability of the learned features and classifier.

The DL framework in this paper extends a number of convolutional neural networks (CNN) for visual semantic analysis of tumor regions for diagnosis support. The CNN is trained over a large amount of image patches (tissue regions) from WSI to learn a hierarchical part-based representation. The method was evaluated over a WSI dataset from 162 patients diagnosed with IDC. 113 slides were selected for training and 49 slides were held out for independent testing. Ground truth for quantitative evaluation was provided via expert delineation of the region of cancer by an expert pathologist on the digitized slides. The experimental evaluation was designed to measure classifier accuracy in detecting IDC tissue regions in WSI. Our method yielded the best quantitative results for automatic detection of IDC regions in WSI in terms of F-measure and balanced accuracy (71.80%, 84.23%), in comparison with an approach using handcrafted image features (color, texture and edges, nuclear textural and architecture), and a machine learning classifier for invasive tumor classification using a Random Forest.

V. PROPOSED SYSTEM

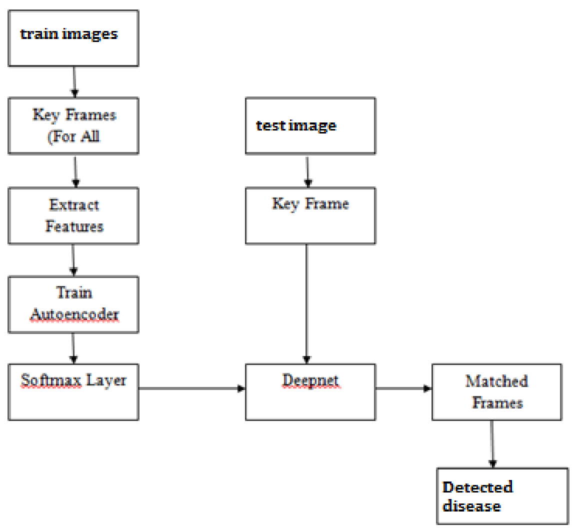

Fig 5.1.Block diagram of proposed work

There are basically 5 steps for proposed work as,

1. Preprocessing: select Images preprocess on it.

2. Key Frame Selection: select limited frame for fast analysis

3. Training: Neural Network by Autoencoders

4. Forming Deep Network Structure

5. Testing*:* Select a query image and Test (NN classifier)

We developed proposed work using deep community informed utilizing auto encoders. Encoded information shall be analyzed utilizing softmaxlayer to be able to mix the equivalent style of knowledge in one workforce. The selected data or trying out knowledge will likely be instantly furnished to deep network fashioned by way of autoencoders so they can examine the checking out information in which layer it lies and the label for the chosen layer will retrieve the an identical style of the info from database. The retrival is situated on colour and texture features of the chosen video and its frames.

Deepnetwork

Deep gaining skills of (moreover referred to as deep centered gaining advantage of or hierarchical gaining abilities of) is a part of a broader own loved ones of approach learning techniques headquartered utterly on getting to grasp files representations, in location of challenge-detailed algorithms. Learning can also be supervised, semi-supervised or unsupervised.

Deep learning architectures together with deep neural networks, deep proposal networks and recurrent neural networks had been applied to fields together with laptop innovative and prescient, speech fame, natural language processing, audio fame, social community filtering, device translation, bioinformatics, drug design, scientific photo analysis, fabric inspection and board sport functions, where they have produced outcome much like and in a number of circumstances superior to human specialists. Deep getting to know models are vaguely influenced via documents processing and verbal exchange patterns in organic fearful constructions however have numerous differences from the structural and purposeful residences of organic brains (by and large human brains), which cause them to incompatible with neuroscience evidences.

Autoencoders:

With the help of coaching information we will educate the neural community utilizing autoencoders. Autoencoders will encode the expertise in specific structure which may also be simply analyzed through network. On this progress we used autoencoder twice to get better accuracy and not more false rejection ratio. As video is nothing however frames of images we can work on the frames to retrieve movies.

Softmaxlayer:

In arithmetic, the softmax characteristic, additionally referred to as softargmax[1] or normalized exponential characteristic,[2]:198 is a function that takes as enter a vector of k actual numbers, and normalizes it into a probability distribution inclusive of ok possibilities. That is, earlier to utilizing softmax, a couple of vector components might be horrible, or a couple of; and might not sum to one; nevertheless after applying softmax, each element might be inside the c application language period displaystyle (zero,1) (0,1), and the components will add up to one, so they may be able to be interpreted as possibilities. Moreover, the greater input additives will correspond to better chances. Softmax is in most cases utilized in neural networks, to map the non-normalized output of a group to a opportunity distribution over envisioned output coaching.

The call "softmax" is deceptive; the perform is not a soft most (a gentle approximation to the highest characteristic), however is then again a easy approximation to the arg max characteristic: the operate whose price is which index has the maximum. In truth, the time interval "softmax" is also used for the closely related LogSumExpfunction, that may be a delicate most. For this rationale, just a few select the bigger accurate time interval "softargmax", but the term "softmax" is conventional in machine gaining knowledge of. For this section, the time period "softargmax" is used to stress this interpretation.

VI. METHODOLOGY

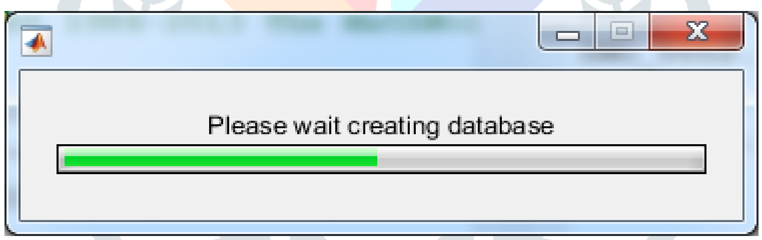

Fig.1 creating both training and testing database using program to_create_database

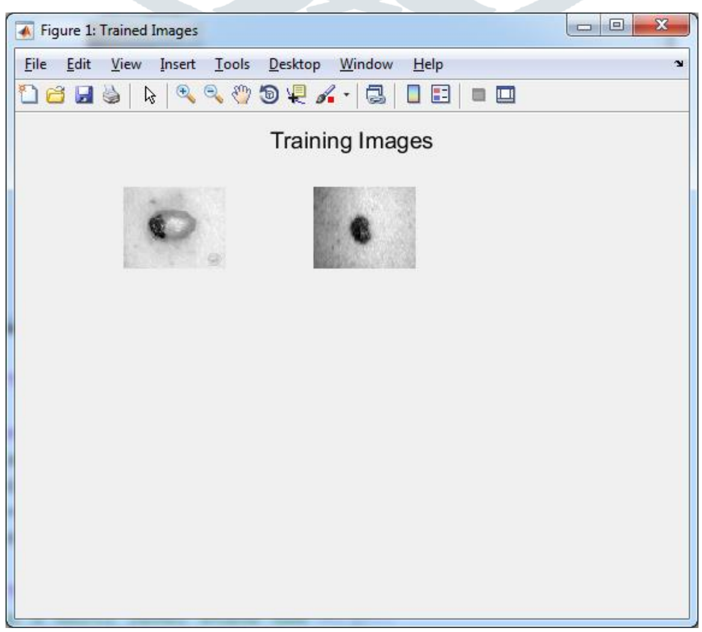

Fig.2 Training Images (1st image is trained as dermis and 2nd is as dermQUEST)

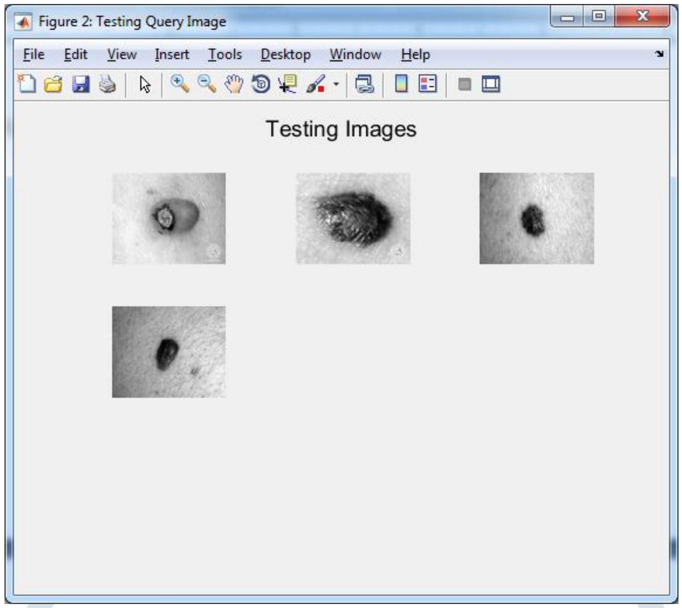

Fig.3 Multiple images are used for testing which are query images.

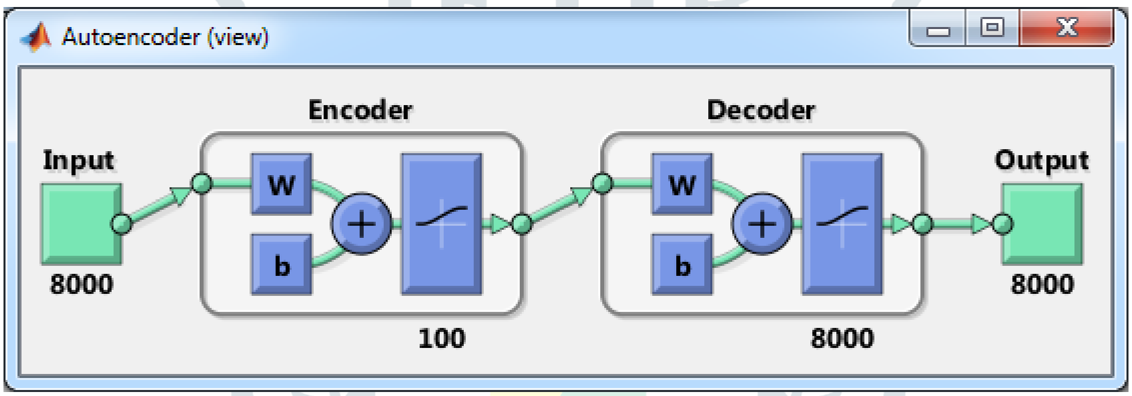

Fig.4 Autoencoder for deep network at 1st level

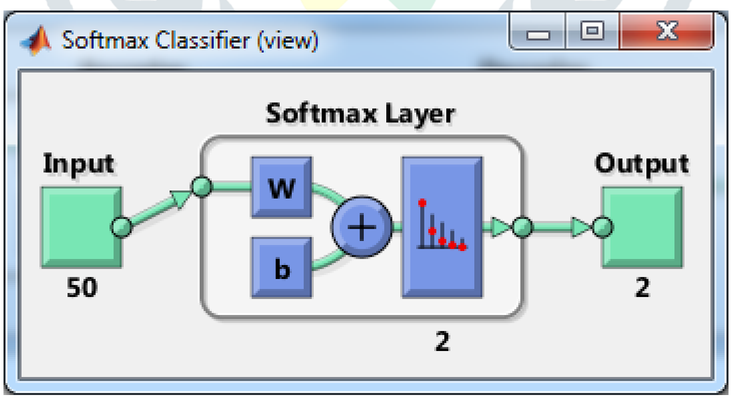

Fig.5 Softmaxlayer for data encoded

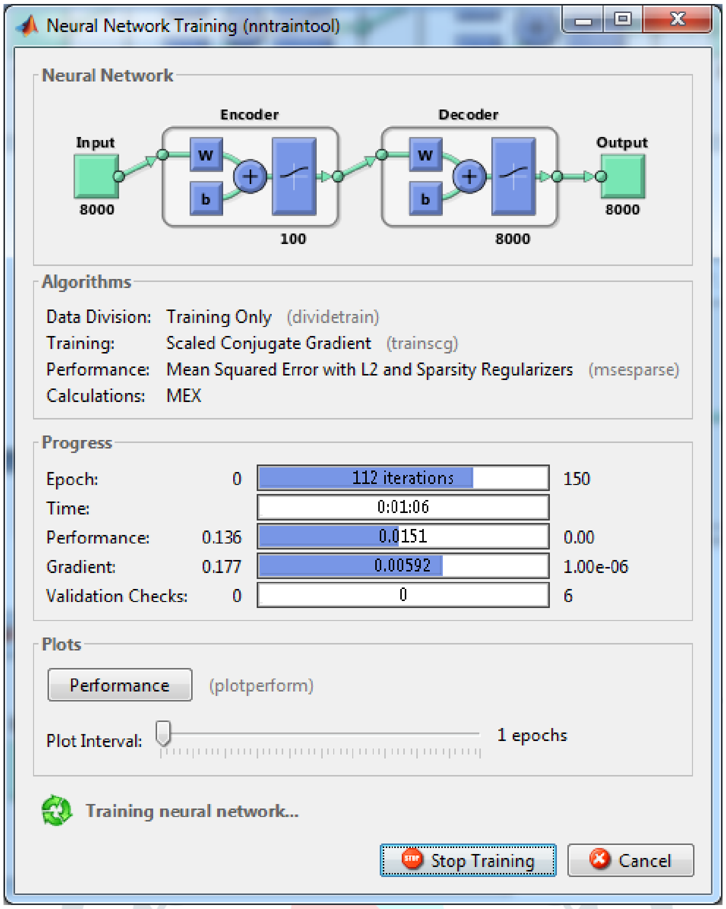

Fig.6 Performing the neural network operations

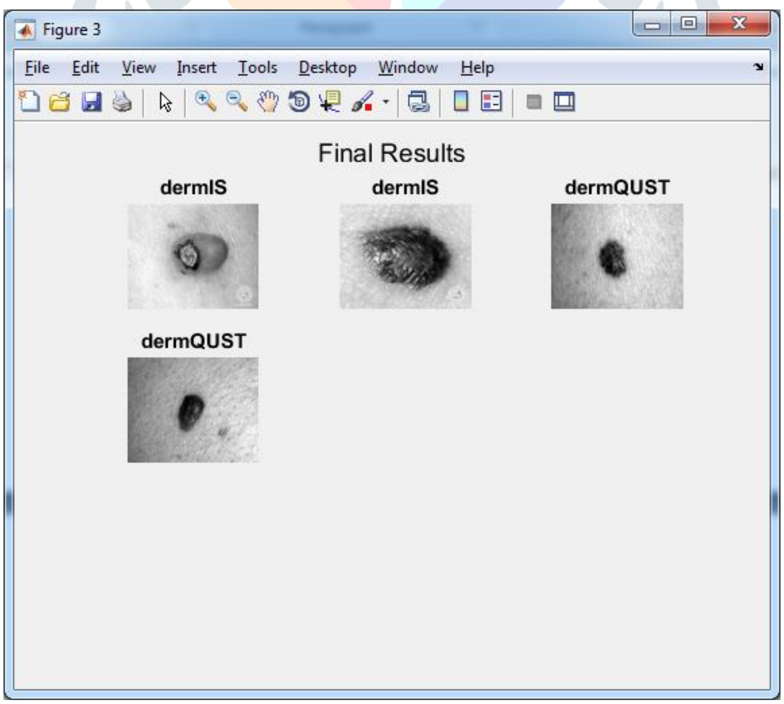

Fig. 7 Finally testing images are detected and classified under dermis and DermQUEST

CONCLUSION

Proposed work is developed and analyzed using Matlab software. The system consists of 2 auto encoders and 1 stack used for deep leaning. Lot of skin diseases are common nowadays because of different infection to body. Proposed work will demonstrate the classification of skin diseases using proposed implementation using MATLAB. Matlab is one of the leading software which help us to design and analyze proposed system for skin disease classification. We used deep learning algorithm for skin disease classification which is based on auto encoders. Two level auto encoder shows better performance compared to the existing state of art techniques. Proposed system is analyzed by both subjective and objective analysis and proved that proposed work performs better in case of huge dataset also.

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[4] Y. Bengio, A. Courville, and P. Vincent. Representation learning: A review and new perspectives. IEEE Trans. Pat- tern Anal. Mach. Intell., 35(8):1798–1828, Aug. 2013.

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