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A Cloud Approach for Melanoma Detection Based on Deep Learning Networks

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ABSTRACT: The purpose of computer vision methods, machine learning, and deep learning in the age of digital pictures is to extract information from them and develop new knowledge. This permits the use of pictures for the early detection and treatment of a broad spectrum of disorders. Deep neural networks are utilised in dermatology to discriminate between melanoma and non-melanoma pictures. We have highlighted two critical elements in melanoma detection research in this work. The first consideration is how even little changes to the parameters in the dataset affect the accuracy of classifiers. In this situation, we looked into Transfer Learning problems. Based on the findings of the first study, we propose that continuous training-test iterations are required to produce robust prediction models. The second argument is the need for a more adaptable system design that can deal with changes in training datasets. In this context, we suggested creating and deploying a hybrid architecture based on Cloud, Fog, and Edge Computing to deliver a Melanoma Detection service based on clinical and dermoscopic pictures. At the same time, this architecture must cope with the volume of data to be studied by shortening the continuous retrain's running time. Experiments on a single computer and several distribution methods have underlined this point, demonstrating how a distributed strategy ensures output attainment in a considerably more adequate period.

***Keywords** –Fog and Edge Computing, Deep Learning Networks*

1. INTRODUCTION

Melanoma is a dangerous kind of skin cancer that develops from melanocytes, the epidermal cells responsible for the synthesis of melanin pigment. Although this kind of tumour accounts for a small proportion of all cutaneous malignancies, it is the leading cause of death [1]. Skin melanoma has grown rapidly in the previous 30 years, however increases differ by age group. Between 2007 and 2016, the rate for those under 50 declined by 1.2% each year, while the rate for those 50 and over grew by 2.2% per year. According to the American Cancer Society, 100350 new cases and 6850 fatalities in both sexes are expected in the United States alone in 2020. 1 The literature is well aware that early detection of melanoma remains a difficulty [2]. The attestation of a right diagnosis is also dependent on the physician's ability to differentiate between various kinds of skin lesions based on his level of expertise. The biopsy is still the ultimate word on a terrible diagnosis. The relevance of early melanoma detection has grown in recent years, particularly in patients who are at high risk of getting cancer, allowing for a higher cure rate. In general, a dermatologist's initial visual examination is utilised to detect melanoma, frequently with the use of polarised light magnification dermoscopy [3]. Technology has the potential to radically alter people's perceptions of medicine while also playing an important part in sophisticated diagnostics systems in determining patient-care choices [4]. The essential features of the decision-making process, however, must not be overlooked: the solution to the clinical issue is inextricably linked to medical research, and therefore to the physicians' experience. Only via collaboration between technology and medical actors can the final product be assured to be of high quality.

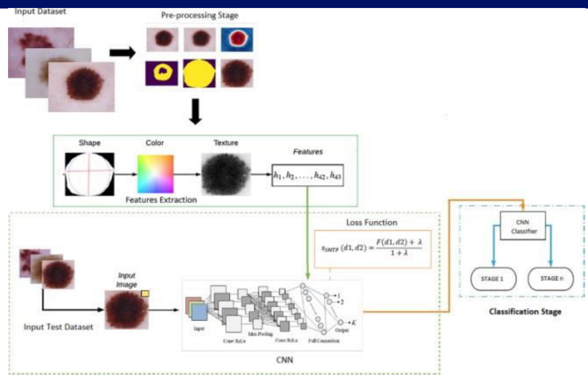

Fig.1: Example figure

Many different forms of computer software have been created in recent years to assist dermatologists in better (and faster) determining if a skin lesion is, is not, or might become a melanoma [1]. There are now several ideas for a computer-aided system for dermatology [5] [6], however despite promises about AI outperforming physicians, there are many additional obstacles that remain. The majority of this programme is concerned with computer vision methods such as boundary identification, symmetry/asymmetry analysis, colour analysis, and dimension detection [5]. Other forms of information, such as Electronic Health Records (EHR), are also used by certain technologies to increase prediction accuracy. Overall, existing melanoma detection methods must account for the complexity of the pictures to be processed, which may result in challenges such as uneven fuzzy lesions borders, noise and artefact presence, low contrast, or poor image illumination [7].

2. LITERATURE REVIEW

Dermatologist-level classification of skin cancer with deep neural networks (https://www.nature.com/articles/nature21056)

Authors: A. Esteva et al

Abstract: Skin cancer, the most prevalent kind of human malignancy, is generally detected visually, starting with a clinical screening and perhaps followed by dermoscopic analysis, a biopsy, and histological investigation. Because of the fine-grained heterogeneity in the appearance of skin lesions, automated categorization of skin lesions using photographs is a difficult problem. Deep convolutional neural networks (CNNs) have shown promise for broad and highly variable tasks over a wide range of fine-grained object categories. We show how to classify skin lesions using a single CNN trained end-to-end using photos with just pixels and illness labels as inputs. We train a CNN using 129,450 clinical pictures, which is two orders of magnitude greater than prior datasets and contains 2,032 distinct illnesses. We compare its performance to that of board-certified dermatologists on biopsy-proven clinical pictures of keratinocyte carcinomas vs benign seborrheic keratoses and malignant melanomas versus benign nevi. The first scenario involves identifying the most prevalent malignancies, while the second involves identifying the worst skin cancer. The CNN outperforms all tested specialists in both tests, indicating that artificial intelligence is capable of identifying skin cancer with the same degree of competence as dermatologists. Mobile devices equipped with deep neural networks have the potential to expand dermatologists' reach outside the clinic. It is estimated that 6.3 billion smartphone subscriptions will exist by 2021, possibly providing low-cost universal access to crucial diagnostic care.

Early diagnosis of cutaneous melanoma: Revisiting the ABCD criteria

The prevalence of cutaneous melanoma has risen in recent decades, making early detection a significant public health issue. The ABCD (Asymmetry, Border irregularity, Color variegation, Diameter >6 mm) acronym for cutaneous pigmented lesions was developed in 1985 and has been extensively used, but it needs to be revisited in light of new evidence on the presence of small-diameter (or =6 mm) melanomas. Evidence gathering: Cochrane Library and PubMed searches were undertaken from 1980 to 2004 using the search phrases ABCD, melanoma, and small-diameter melanoma. Bibliographies of retrieved articles were also utilised to find further relevant material. Synthesis of evidence: The available results do not justify decreasing the ABCD diameter threshold from the present higher than 6 mm recommendation. The findings, on the other hand, justify expanding to ABCDE to stress the importance of developing pigmented lesions in the natural history of melanoma. Physicians and patients with nevi should keep an eye out for changes in size, shape, symptoms (itching, discomfort), surface (particularly

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bleeding), and colour shades. The ABCD criteria for the gross examination of pigmented skin lesions and the early detection of cutaneous melanoma should be enlarged to ABCDE (to include "evolving"). At this time, no changes to the current diameter requirement are necessary.

Dermatological expert system implementing the ABCD rule of dermoscopy for skin disease identification

Doctors and radiologists commonly use the ABCD rule of dermoscopy to distinguish between malignant and benign skin lesions. The assessment of the dermoscopic score only by visual examination may result in an incorrect diagnosis of the illness at an early stage. The ABCD features were improved and quantified in a dermatological expert system (DermESy) for the distinction of malignant and benign lesions in this study. DermESy, a rule-based expert system, was created by combining dermatological expertise with accurate quantification of dermoscopic data. DermESy was used to classify dermoscopic pictures as malignant, benign, or suspicious based on the estimated total dermoscopic score (TDS), which was consistent with expert results. Shape, brightness, and colour changes are examined to adjust the 'A' score in order to estimate the TDS. The colour information extraction method is used to extract important colour patches in order to calculate the 'C' score. Dermoscopic structures segmentation algorithms have been devised to determine the proper 'D' score of a skin lesion. The ABCD rule of dermoscopy has been modified in this study by taking into account the spatial features of dermoscopic structures for better diagnosis of malignant lesions. DermESy has an explanatory subsystem to aid the dermatologist with accurate in-depth visualisation. DermESy has 97.69% sensitivity, 97.97% specificity, and 97.86% accuracy in distinguishing benign and malignant skin lesions. To prove the reliability and robustness of the proposed system, the TDS scored by DermESy is confirmed and compared to professional dermatologists' TDS ratings of the identical dermoscopy pictures.

Computer-aided decision support for melanoma detection applied on melanocytic and nonmelanocytic skin lesions: A comparison of two systems based on automatic analysis of dermoscopic images

Only melanoma is detected by commercially available clinical decision support systems (CDSSs) for skin cancer. The systems' correct usage requires expert knowledge, limiting their value to nonexperts. Furthermore, no technologies exist to identify nonmelanoma skin cancer, which is the most frequent kind of skin cancer (NMSC). Because early detection of skin cancer is critical, a CDSS that is relevant to all kinds of skin lesions and acceptable for nonexperts is required. The authors are working on a CDSS called Nevus Doctor (ND). We look at ND's ability to identify melanoma and NMSC, as well as potential improvements. ND examined an independent test set of 870 dermoscopic pictures of skin lesions, including 44 melanomas and 101 NMSCs. Using the same set of lesions, its sensitivity to melanoma and NMSC was compared to that of Mole Expert (ME), a commercially available CDSS. ME and ND were both sensitive to melanoma. At 95% melanoma sensitivity, ND had 100% NMSC sensitivity and 12% specificity. ME properly identified the melanomas misclassified by ND with 95% sensitivity, and vice versa. ND can detect NMSC without compromising melanoma sensitivity.

Artificial intelligence-based image classification methods for diagnosis of skin cancer: Challenges and opportunities:

There has recently been a lot of interest in creating Artificial Intelligence (AI) enabled computer-aided detection systems for skin cancer. With the rising prevalence of skin malignancies, a lack of awareness among a growing population, and a lack of competent clinical competence and resources, there is an urgent need for AI systems to support doctors in this sector. A huge amount of skin lesion datasets are publically accessible, and researchers have created AI solutions, notably deep learning algorithms, to differentiate malignant from benign skin lesions in several picture modalities such as dermoscopic, clinical, and histopathological images. Despite claims that AI systems can classify skin lesions more accurately than dermatologists, these AI systems are still in the very early phases of clinical application and are not yet suitable to assist clinicians in the detection of skin malignancies. In this study, we cover achievements in digital image-based AI solutions for skin cancer

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detection, as well as potential difficulties and future prospects to improve these AI systems to help dermatologists identify skin cancer.

Detection of melanoma from skin lesion images using deep learning techniques:

Cancer arises when cells in any region of the body begin to proliferate uncontrollably. It has the potential to spread to other places of the body. Melanoma is a kind of skin cancer that develops when melanocytes, or cells that create melanin (the pigment responsible for the apparent colour of skin), proliferate uncontrollably. Melanoma is harmful because it has a high proclivity to spread to other places of the body if not diagnosed and treated early. In this research, we apply deep learning methods to create a classification system that can distinguish between malignant and benign skin lesions. This approach is based on a collection of skin lesion photos from different locations on the body. We enhance the dataset with suitable changes and assess the classification system using a variety of measures. The many models utilised in this implementation are compared using metrics to determine the best performing model. ResNet-50 outperforms the other two in terms of sensitivity, specificity, and accuracy, with values of 99.7%, 55.67%, and 93.96%, respectively.

3. METHODOLOGY

Current melanoma detection algorithms must account for the complexity of the pictures to be processed, which may result in challenges such as uneven fuzzy lesions borders, noise and artefact presence, low contrast, or poor image illumination.

Disadvantages:

- The first is linked to the amount of storage space and significant computation required to train a complicated model on massive datasets in order to attain acceptable performance.
- The second disadvantage is the time and effort necessary to maintain one or more models up to date.

We have highlighted two critical elements in melanoma detection research in this work. The first consideration is how even little changes to the parameters in the dataset affect the accuracy of classifiers.

Advantages:

- A distributed strategy ensures output completion in a significantly shorter period of time.
- To build strong prediction models, we believe that continual training-test iterations are required.

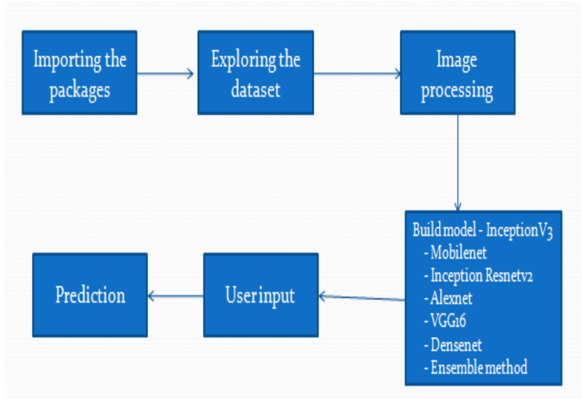

Fig.2: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- Data exploration: we will input data into the system using this module;
- Processing: we will read data for processing using this module.
- Data splitting into train and test: Using this module, data will be split into train and test.
- Model generation: Create models based on InceptionV3, Mobilenet, Inception Resnetv2, Alexnet, VGG16, Densenet, and Ensemble models, and compute accuracy values.
- User signup & login: Using this module will result in registration and login.
- User input: Using this module will result in prediction input.
- Prediction: final predicted displayed.

4. IMPLEMENTATION

InceptionV3:

Inception v3 is a convolutional neural network that was developed as a Googlenet module to aid with picture processing and object recognition. It is the third version of Google's Inception Convolutional

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Neural Network, which was first unveiled as part of the ImageNet Recognition Challenge. Inceptionv3 was designed to allow for deeper networks while also reducing the number of parameters from being too large: it has "under 25 million parameters," compared to AlexNet's 60 million.

Mobilenet:

Depthwise separable convolutions are used by MobileNet. When compared to the network with ordinary convolutions of the same depth in the nets, it greatly lowers the number of parameters. As a consequence, lightweight deep neural networks are created. Two procedures are used to create a depthwise separable convolution.

Inception Resnetv2:

Inception-ResNet-v2 is a convolutional neural network that extends the Inception family but includes residual connections (replacing the filter concatenation stage of the Inception architecture).

Alexnet:

The term AlexNet refers to a convolutional neural network that has had a significant influence on the area of machine learning, particularly in the application of deep learning to machine vision. It notably won the 2012 ImageNet LSVRC-2012 competition by a wide margin (15.3% vs. 26.2% error rates in second place).

VGG16:

VGG16 is a convolution neural net (CNN) architecture that won the 2014 ILSVR (Imagenet) competition. It is regarded as one of the best vision model architectures to date.

Densenet:

A DenseNet is a form of convolutional neural network that uses dense connections between layers through Dense Blocks, which link all layers (with matching feature-map sizes) directly. To maintain the feed-forward nature, each layer receives extra inputs from all previous levels and passes on its own feature-maps to all following layers.

Ensemble method:

Ensemble methods are strategies for enhancing model accuracy by mixing numerous models rather of utilising a single model. The integrated models considerably improve the accuracy of the findings. As a result, ensemble approaches in machine learning have grown in favour.

5. EXPERIMENTAL RESULTS

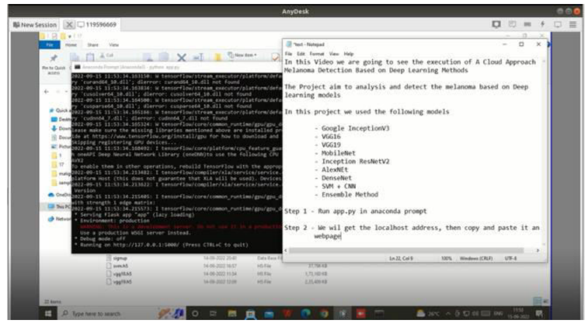

Fig.3: Webpage loading

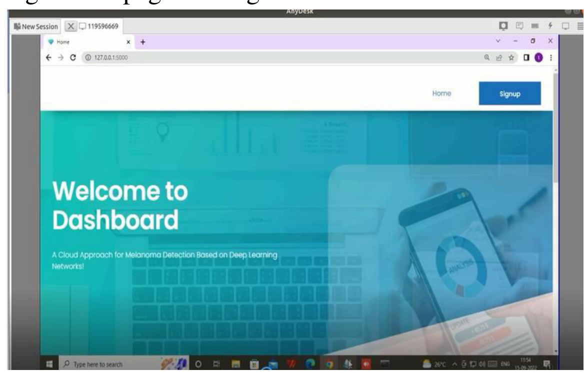

Fig.4: Home screen

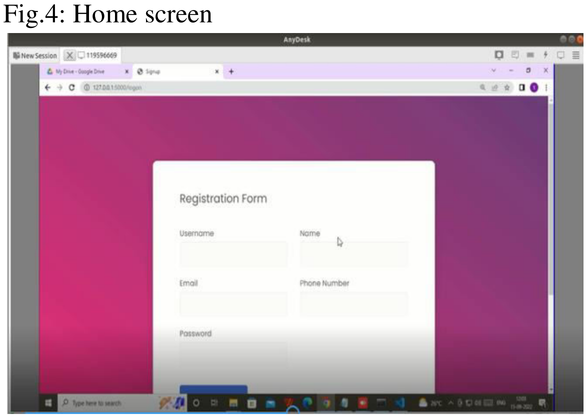

Fig.5: User signup

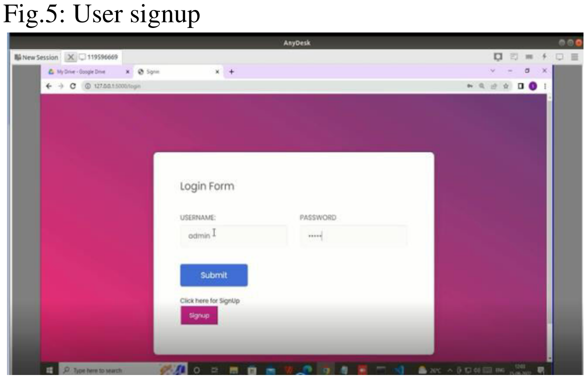

Fig.6: User login

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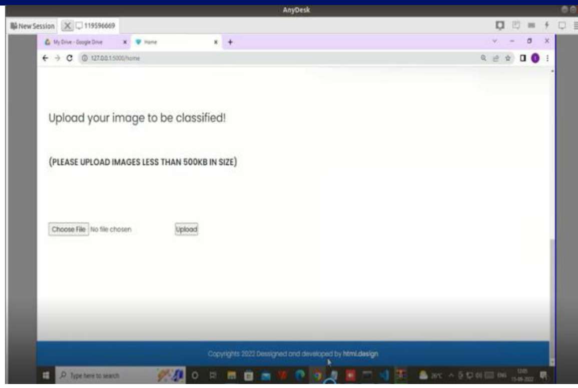

Fig.7: Main screen

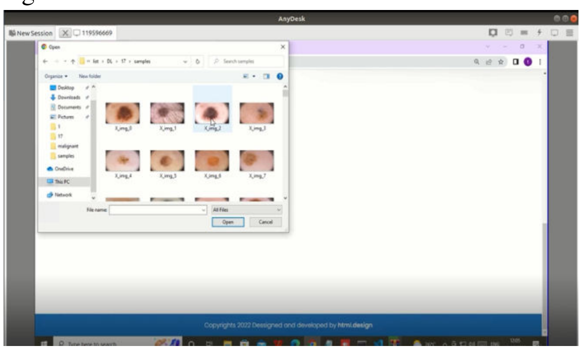
Fig.8: Input images

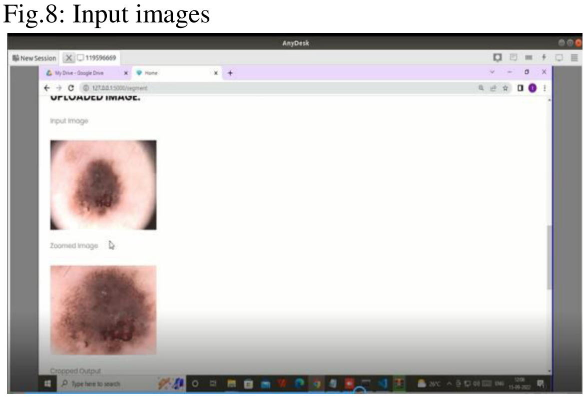
Fig.9: Classification of images

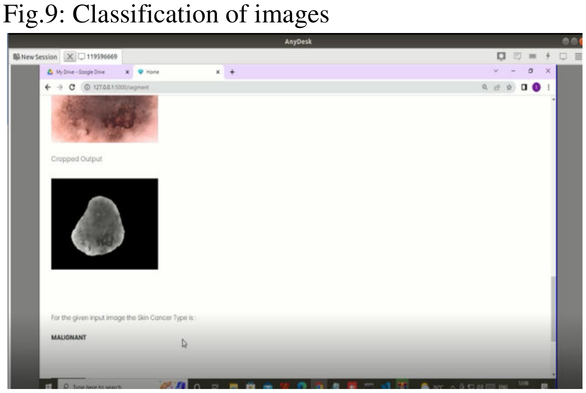

Fig.10: Prediction result

6. CONCLUSION

Despite the great performance claimed in the literature, the data provided in this paper imply that the Transfer Learning technique, which is widely used currently, may not be dependable. The findings of the first experiment, in particular, illustrate that even little modifications to the original training dataset may significantly reduce classifier performance. These findings are consistent with what was previously reported in [5]. Our findings also indicate that AlexNet is the most robust network in terms of Transfer Learning. Furthermore, without segmentation or data augmentation, all of the CNN networks utilised achieved a higher average ACC. Continuous retraining is essential to reduce performance decline because to the huge number of training reiterations required to obtain the best classifier. As a consequence of these results, we conducted the second experiment, which enabled continuous retraining using a Cloud/Fog/Edge design. We were able to save up to 76% of computing time by performing the ongoing retraining phase required to keep the classifier robust. As a result, we can deduce that envisioning a distributed architecture could provide several benefits to the end user by allowing: data collection and aggregation "on the network" to support early melanoma diagnosis, enriching image databases with new knowledge; processing critical data locally, at the network's Edge, with local data storage, resulting in reduced data processing latency, real-time response, lower bandwidth, and faster data access. In the pre-processing and categorization of melanoma pictures, this form of architecture implementation responds to a fresh need and data management approaches that are more favourable than standard methods. It handles the problem of transferring photos to a central data server or Cloud service for processing in particular. Furthermore, decentralising them improves capacity and, as a consequence, computation times. The following diagram depicts the overall functionality of the suggested hybrid architecture. Data buckets are kept on the Cloud, and system training is carried out. After each formation in the Fog region, where services are performed, the orchestrator is in charge of distributing the optimised services. Local computations are conducted in the

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Edge region on IoMT devices (for example, smartphones). HiC-Otsu is a software component of the Fog system on the IoMT device that conducts early data processing. To enhance system performance, the QoS moderator annotates material. The generic user uses the output of services, but by loading data, he adds to the system's knowledge base.

7. FUTURE WORK

Based on our findings, we want to develop more robust neural network models to learn from pictures in the future (and generalise from them). According to our findings, CNN networks performed better when no segmentation was applied. This research suggests that skin around lesions may provide essential information that should be considered during training. Experiment one should be repeated, this time examining alternative pre-processing procedures. We were unable to predict the smallest training step required to achieve satisfactory robustness. Future research should look at this element in order to optimise training time. The second experiment examines how a dispersed environment may benefit in time savings (both RT and clock time). A more thorough examination of the distributed architecture might be conducted to see if more complicated design can increase performance.

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