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DETECTION OF BLOOD CANCER

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ABSTRACT:

Leukemia is a fatal disease that threatens the lives of many patients. Early detection can effectively improve its rate of remission. This paper proposes two automated classification models based on blood microscopic images to detect leukemia by employing transfer learning, rather than traditional approaches that have several disadvantages. In the first model, blood microscopic images are pre-processed; then, features are extracted by a pre-trained deep convolutional neural network MODELS, which makes classifications according to numerous well-known classifiers. In the second model, after pre-processing the images, neural network models are fine-tuned for both feature extraction and classification. Experiments were conducted on a dataset consisting of different images confirming that the second model performs better than the first because of 100% classification accuracy.

Keywords: *Convolution neural network*

1. INTRODUCTION

Diagnosis is performed by a physician to detect the presence or absence of a certain disease in a patient according to a particular dataset, which may include signs, symptoms, medical images, and exams. An incorrect diagnosis can have adverse consequences, for example, prescription of drugs with side effects, on a patient's health. As well as increasing the costs of treatment, incorrect diagnoses may complicate treatment procedures. To help physicians achieve high diagnostic accuracy, many assistant systems were proposed. Many diseases, including glaucoma, skin cancer, breast cancer, and leukemia are already addressed by such systems. Early and accurate diagnoses could effectively reduce treatment costs, increase the probability of remission, or even prolong the lives of patients. Leukemia is a common fatal disease that threatens the lives of many teenagers and children. Infants younger than five years of age are at increased risk. A 2012 study showed that about 352,000 adults and children all over the world develop leukemia, which starts in the bone marrow and is distinguished by the number of white cells increasing in an abnormal manner.

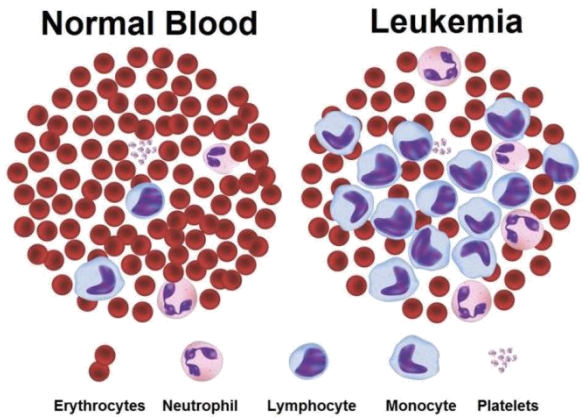

Fig.1: Example for detection

This disease has several causes, such as exposure to radiation and certain chemicals, as well as family history. Diagnoses can be performed via a variety of tests, such as physical examination, blood test, blood count, and bone marrow biopsy. Microscopic analysis is considered the most cost-effective procedure for initial diagnoses, but it is usually performed manually by an operator who is vulnerable to fatigue that could result from having to perform many tests in a single day. Moreover, such manual diagnoses are unreliable in themselves, as they are tedious, time-consuming, and subject to inter-observer variations. Hence, there is a need to build automated, low-cost systems that can differentiate between healthy and unhealthy blood smear images with high accuracy but without manual intervention.

2. LITERATURE REVIEW

2.1 Diagnosing leukemia in blood smear images using an ensemble of classifiers and pre-trained convolutional neural networks

Leukemia is a worldwide disease. In this paper we demonstrate that it is possible to build an automated, efficient and rapid leukemia diagnosis system. We demonstrate that it is possible to improve the precision of current techniques from the literature using the description power of well-known Convolutional Neural Networks (CNNs). We extract features from a blood smear image using pre-trained CNNs in order to obtain an unique image description. Many feature selection techniques were evaluated and we chose PCA to select the features that are in the final descriptor. To classify the images on healthy and pathological we created an ensemble of classifiers with three individual classification algorithms (Support Vector Machine, Multilayer Perceptron and Random Forest). In the tests we obtained an accuracy rate of 100%. Besides the high accuracy rate, the tests showed that our approach requires less processing time than the methods analyzed in this paper, considering the fact that our approach does not use segmentation to obtain specific cell regions from the blood smear image.

2.2 Glaucoma detection based on deep convolutional neural network

Glaucoma is a chronic and irreversible eye disease, which leads to deterioration in vision and quality of life. In this paper, we develop a deep learning (DL) architecture with convolutional neural network for automated glaucoma diagnosis. Deep learning systems, such as convolutional neural networks (CNNs), can infer a hierarchical representation of images to discriminate between glaucoma and non-glaucoma patterns for diagnostic decisions. The proposed DL architecture contains six learned layers: four convolutional layers and two fully-connected layers. Dropout and data augmentation strategies are adopted to further boost the performance of glaucoma diagnosis. Extensive experiments are performed on the ORIGA and SCES datasets. The results show area under curve (AUC) of the receiver operating characteristic curve in glaucoma detection at 0.831 and 0.887 in the two databases, much better than state-of-the-art algorithms. The method could be used for glaucoma detection.

2.3 Multi-Resolution-Tract CNN with Hybrid Pretrained and Skin-Lesion Trained Layers

Correctly classifying a skin lesion is one of the first steps towards treatment. We propose a novel convolutional neural network (CNN) architecture for skin lesion classification designed to learn based on information from multiple image resolutions while leveraging pretrained CNNs. While traditional CNNs are generally trained on a single resolution image, our CNN is composed of multiple tracts, where each tract analyzes the image at a different resolution simultaneously and learns interactions across multiple image

resolutions using the same field-of-view. We convert a CNN, pretrained on a single resolution, to work for multi-resolution input. The entire network is fine-tuned in a fully learned end-to-end optimization with auxiliary loss functions. We show how our proposed novel multi-tract network yields higher classification accuracy, outperforming state-of-the-art multi-scale approaches when compared over a public skin lesion dataset.

2.4 Deep learning for identifying metastatic breast cancer.

The International Symposium on Biomedical Imaging (ISBI) held a grand challenge to evaluate computational systems for the automated detection of metastatic breast cancer in whole slide images of sentinel lymph node biopsies. Our team won both competitions in the grand challenge, obtaining an area under the receiver operating curve (AUC) of 0.925 for the task of whole slide image classification and a score of 0.7051 for the tumor localization task. A pathologist independently reviewed the same images, obtaining a whole slide image classification AUC of 0.966 and a tumor localization score of 0.733. Combining our deep learning system's predictions with the human pathologist's diagnoses increased the pathologist's AUC to 0.995, representing an approximately 85 percent reduction in human error rate. These results demonstrate the power of using deep learning to produce significant improvements in the accuracy of pathological diagnoses.

3. IMPLEMENTATION

Many traditional computer-aided systems use image processing and machine-learning techniques that usually involve several steps, including pre-processing, segmentation, feature extraction, and classification. However, the success of each step depends on the success of the preceding step. For example, the success of classification depends on the success of the preceding feature extraction, which itself depends on the success of the preceding segmentation. Hence, high classification accuracy requires the success of all steps, each of which is non-trivial and problem-dependent.

Disadvantages:

1. High classification accuracy requires the success of all steps.

This paper proposes two classification models that are based on transfer learning and can distinguish between healthy and unhealthy blood smear images with high accuracy. These models employ RESNET50, which is a deep CNN that achieved huge success in the image classification challenge, ImageNet.

Advantages:

1. High accuracy.

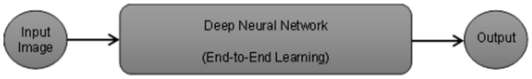

Fig.2: System architecture

Classification models are proposed here to distinguish between microscopic images depicting healthy tissue and leukemia. Transfer learning was adopted for both models, which employed pre-trained deep neural networks. Transfer learning eliminates the time and effort needed to design and train such networks from scratch. According to Castelluccio et al., there are two methods to apply transfer learning. The first method includes obtaining features extracted from the input images by obtaining the values of the last fully connected layer (FC) of the net, before using another classifier for classification. The second method involves modifying the structure of the network by eliminating the high-level layers. This process is known as network fine-

tuning. In this study, methods were adopted and implemented by our proposed models.

4. ALGORITHMS

DENSENET:

A DenseNet is a type of convolutional neural network that utilises dense connections between layers, through Dense Blocks, where we connect all layers (with matching feature-map sizes) directly with each other.

DenseNet is a new CNN architecture that reached State-Of-The-Art (SOTA) results on classification datasets (CIFAR, SVHN, ImageNet) using less parameters. Thanks to its new use of residual it can be deeper than the usual networks and still be easy to optimize.

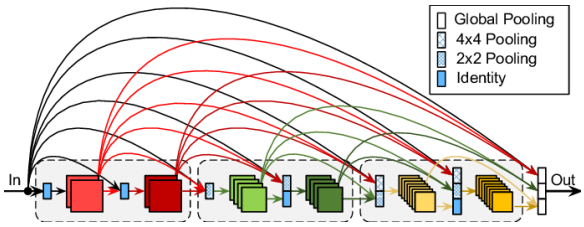

Fig.3: DenseNet model

INCEPTION RESNET V2:

Inception-ResNet-v2 is a convolutional neural architecture that builds on the Inception family of architectures but incorporates residual connections Inception-ResNet-v2 is a convolutional neural network that is trained on more than a million images from the ImageNet database [1]. The network is 164 layers deep and can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

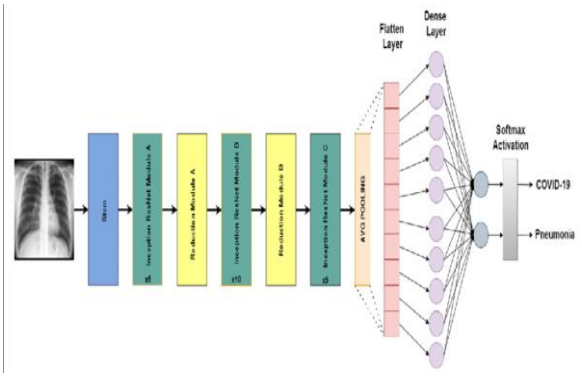

Fig.4: Inception Resnet V2 model

ResNet50 is a variant of ResNet model which has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. It has 3.8 x 10^9 Floating points operations. It is a widely used ResNet model and we have explored ResNet50 architecture in depth. ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

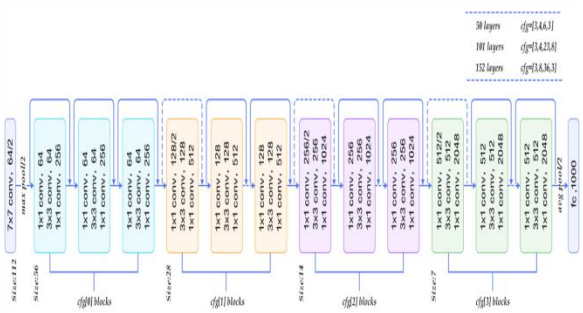

Fig.5: Resnet50 model

5. EXPERIMENTAL RESULTS

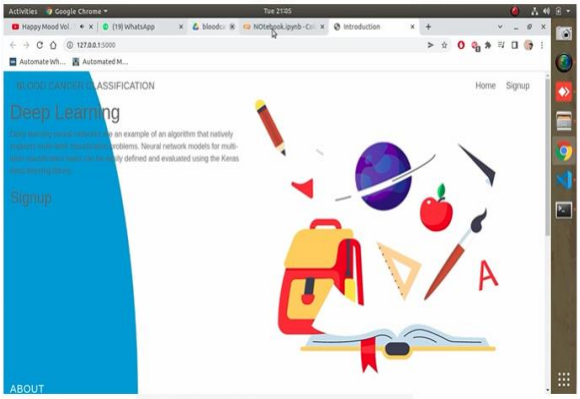

Fig.6: Home page

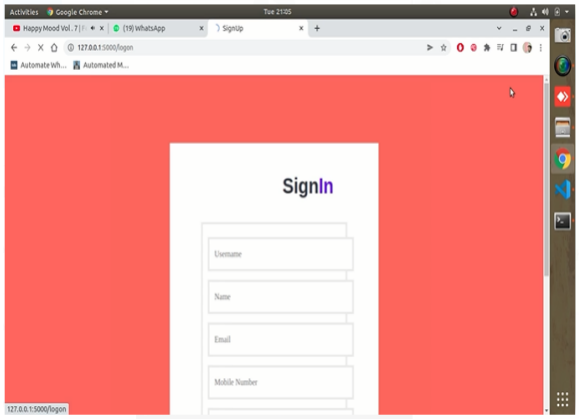

Fig.7: Signin

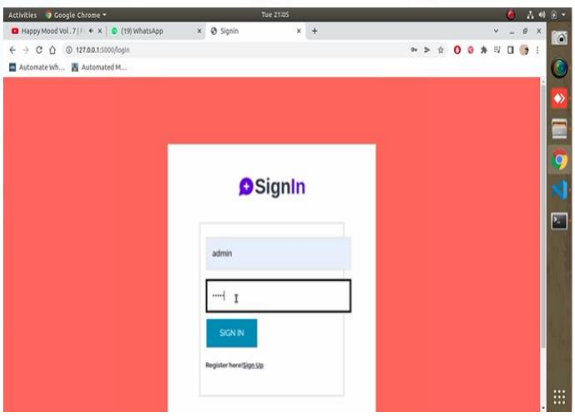

Fig.8: Admin login

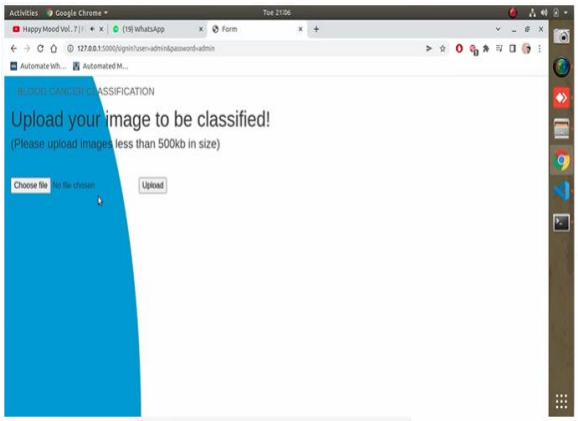

Fig.9: Upload image

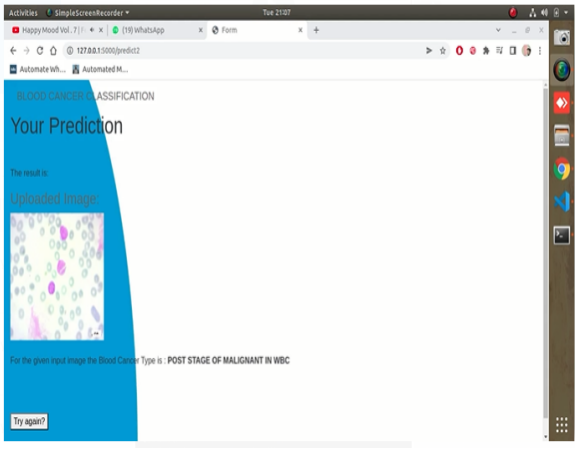

Fig.10: Predict result

6. CONCLUSION

The early detection of leukemia can help effectively in its treatment. This study proposed two classification models distinguishing between leukemia-free and leukemia-affected blood microscopic images. Experiments demonstrated the superiority of the SVM classifier. The second model employs transfer learning models for both feature extraction and classification. Experiments for this model demonstrated its superiority to the first model with respect to various performance metrics.

7. FUTURE SCOPE

A future study could be extended to differentiate among the different types of leukemia rather than simply marking images as leukemia-free or leukemia-affected.

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