IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

DEEP CONVOLUTION NEURAL NETWORK FOR BIGDATA CATHARTIC PICTURE CLASSIFICATION

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ABSTRACT

Cathartic picture classification is critical in clinical teaching and treatment tasks. The conventional method, on the other hand, has already reached its performance limit. Furthermore, their application necessitates a significant investment of time and effort in the extraction and selection of taxonomic features. Deep convolution neural networks are a new machine learning method that has shown promise for a variety of classification tasks. Notably, on various image classification tasks, the agglomeration neural network dominates with the simplest results. However, medical image datasets are difficult to create because labelling them requires a high level of expertise. As a result, this paper investigates the use of a cumulative neural network (CNN) algorithm to classify pneumonia using a chest X-ray dataset. Three techniques were tested experimentally. It is a linear support vector machine classifier with local orientation and rotational freedom functions, and it communicates learning across two cumulative neural network models. Data augmentation is a data pre-processing method that can be used with any or all of the three methods. The results of the tests show that increasing the data is a good way for all three algorithms to improve their performance. Transfer learning, on the other hand, may be a more useful classification method on an extremely small data set than a support vector machine with strongly directed independent key features and binary rotation; however, to improve performance, specific features must be retrained on an alternate target dataset. The second important factor may be the network's relative complexity.

Keywords: DCNN, Big data, deep learning, biomedical image, image analysis.

INTRODUCTION

The classification of cathartic images is critical in clinical care and treatment. For example, chest X-ray analysis is the best way to diagnose pneumonia [1, 2], which kills approximately 50,000 people in the United States each year; however, classifying pneumonia from chest X-rays requires the use of professional radiologists, who may be a scarce and expensive resource in some areas.

Support vector methods (SVMs) and other standard machine learning methods have long been used in medical image classification. However, these methods have the following drawbacks: Their performance is far from satisfactory, and as a result, their development in recent years has been slow. Furthermore, feature extraction and selection are time-consuming and depend on the object.Deep neural networks (DNNs), particularly convolutional neural networks (CNNs), have been widely used in image classification tasks since 2012 [4].

CNN image classification research has produced results comparable to human experts. CheXNet, a CNN with 121 layers trained on a dataset of over 100,000 frontal-view chest X-rays (ChestX-ray 14), outperformed four radiologists on average. Furthermore, Kermany et al. [3] propose a transfer learning system capable of classifying 108,309 optical coherence tomography (OCT) images, with a weighted average error that matches the typical performance of six human experts.

Medical images are difficult to collect because data privacy concerns and the need for time-consuming expert explanations complicate the collection and labelling of medical data. One of the two general paths to resolution is to collect more data, such as through crowdsourcing [5] or digging through existing clinical reports [6]. In a different way, is researching how to improve the performance of a small low dataset, which is critical because the knowledge gained can be applied to large dataset research. Furthermore, the largest published chest X-ray image dataset (ChestX-ray 14) remains far smaller than the largest general image dataset-ImageNet, which reached 14,197,122 instances in 2010 [7, 8].

Because of the proliferation of digital devices and advancements in camera technology The production of medical images is increasing at an exponential rate as technology advances. Digital imaging is now used in modern hospitals to predict the severity of a patient's disease. With Image classification has become a significant challenge with a large number of medical images due to the rapid development of digital imaging. Classification methods are thus required to assign these medical images to the most appropriate class based on their similarity. There are pictures of different organs on the body as calculated tomography (CT-Scans), X-rays (electromagnetic.) waves), positron emission tomography (PET) is a type of Imaging tests help reveal how your organs and tissues are active body in the domain of medical image classification. Another type of scan is magnetic resonance imaging (MRI), which can generate and provide clearly identified information and images about parts of the body, including the brain. Due to the large volume of medical care images, it is nearly impossible for a doctor to classify them manually.

A Brief Introduction to DCNN

A convolutional neural network is made up of a network of artificial neurons that are linked and have biases and weights that can be learned. These neurons are capable of communicating with one another. A properly trained network would response appropriately at that time given an picture or pattern to recognise since the connections' numeric weights are tweaked during the training stage. The network is made up of multiple layers of neurons that can recognise features. Numerous neurons in each layer respond to various combinations of inputs from the layers below them. The layers are constructed such that the previous layer forecasts the group for basic patterns included in a input, next layer finds patterns of patterns, and the last layer finds patterns for these patterns.

The entire clinical workflow is supported by fast and accurate detection, segmentation, and tracking of anatomical structures or pathologies, allowing for real-time guidance, quantification, and processing in the operating room. The majority of cutting-edge solutions for parsing medical images use machine learning methods. While this enables the effective use of massive annotated image databases, such techniques typically have inherent limitations related to the efficiency of scanning high-dimensional parametric spaces as well as the learning of representative features for modelling the article appearance. In this context, we present Marginal Space Deep Learning, a novel framework for volumetric image parsing that leverages the benefits of efficient object parametrization in hierarchical marginal spaces as well as the representational power of cutting-edge deep learning.The system trains classifiers in high-probability clusters. We propose cascaded sparse adaptive neural networks, which learn to focus the networks' information sampling patterns on sparse, context-rich parts of the input, thereby significantly reducing runtime and increasing system robustness. While we show that this method improves performance. The main limitation of the current state-of-the-art is that the looks model training and parameter scanning are completely decoupled as independent algorithmic steps. To address this, we present a system extension that models the thing's appearance as well as parameter search as a unified behavioural task for a man-made agent. Instead of scanning the parameter space exhaustively, the system uses reinforcement learning to find optimal navigation paths, directing the search to the most appropriate location We show that the approach performs significantly better than the state-of-the-art in detecting arbitrary landmarks in ultrasound, resonance, and X-ray data. Our future efforts will be directed toward broadening this framework for generic image parsing.

Literature Review

Literature reviews enable you to become acquainted with current information in your chosen field, as well as the boundaries and boundaries of that field. Literature reviews can also help you understand the theory(ies) driving the field, allowing you to place your search query into context. A Literature Review's Structure The aim provides a brief explanation of the study's aim and purpose. Body: Describe the research subject's or mission's background; compare and assess current knowledge; explain the theoretical framework; identify any contentious issues; list any literature-related roadblocks; and state why the research is being conducted. a theory or set of assumptions that will be investigated Techniques for statistical series and evaluation.A brief paragraph that summarises several key points and arguments.

Medical image classification is a subtopic of image classification. It can also be used with various image classification techniques. Many image enhancement methods, for example, to improve discriminant features for classification [14].

However, because CNN is a complete image classification solution, it will learn the functions on its own. As a result, no literature on how to choose and improve medical imaging features will be reviewed. According to CNN, the exam focuses primarily on using traditional methods and learning transitions.

Recent research trends in medical image classification have now been transferred to DCNN [15]. The author proposed a method for representing objects based on super-dimensional computation using different binary code vectors [13]. The height feature vector is based on a binary system vector with more operations in object vector computation that is beneficial for image classification representation. The author of [17] proposes manually extracting features based on a complex texture and its intensity distribution problem.

The author describes a technique for solving segmentation problems using smooth localization rather than morphological methods. The author of proposed a and effective adversarial learning network feature in his work [19] to take advantage of useful features and troubleshoot overfitting.

A sub-subject of image classification is medical image classification. Many image classification techniques can be applied to it. Many image enhancement methods, for example, are used to improve the discriminable features for classification. However, Because DCNN is a complete image classification solution, it will learn the feature on its own. As a result, the literature on how to choose and enhance features in a medical image will not be reviewed. The review focuses primarily on the use of traditional methods and DCNN-based transfer learning. Furthermore, on the capsule network on medical image related paper to investigate what factors in those models are critical to the final result and the gaps in their work.

Current System

Currently, some of the system as well as the manual method of disease detection are in use. When patients suffer from illnesses such as covid-19, pneumonia, and brain tumours, they have no idea about the illness, and if they want to know about it, they must go to the hospital, where doctors will take X-rays and perform medical checks to identify it.

System Proposal

The proposed model consists of datasets used to predict disease using image classification. In this system, I will use the modules known as the users to predict the disease by utilising some fields.

Benefits of the proposed system:

1. To demonstrate that this method is well suited to classifying a large number of cathartic images of various body organs.

2. To help the doctor understand the symptoms and make better decisions about how to treat them.

DCNN on Cathartic Picture Classification

This is the most important image classification and segmentation challenge in the field of image analysis, with various CNN-based deep neural networks already developed and significant results achieved on ImageNet Challenger [18]. Because DCNN is an excellent feature extraction tool, using it for medical image classification can save time and money on complicated and costly feature engineering. Qing et al. [18] presented a custom DCNN with a shallow ConvLayer for lung disease image plate classification. Furthermore, he discovered that the CNN-based system can be trained using modern chest X-ray (CXR) and film datasets with high accuracy and precision. Highly sensitive datasets, such as Stanford's Diagnostic Radiology dataset, typically contain more than 400,000 CXRs, and a new CXR database is being developed (ChestX-ray8), In face-to-face vision, there are 108,9 8 CXRs [20]. Furthermore, the limited data usage makes training a suitable model difficult. Transfer learning CNNs are therefore widely used in medical image classification tasks. Kermany et al. [3] perform transform learning on a medical image dataset containing 108,312 optical coherence tomography (OCT) images using InceptionV3 with ImageNet-trained weights. They achieved a mean accuracy of 96.6%, sensitivity of 97.8%, and specificity of 97%. The authors also compared the findings to those of six human experts. Most experts achieve high sensitivity but low specificity, whereas a CNN-based system achieves high sensitivity and specificity. Furthermore, the CNN-based system outperformed the two human experts in terms of average weight error measurement. The authors also conducted tests.

The authors also tested their system on a small pneumonia dataset, consisting of about 5,000 images, and achieved an average accuracy of 92.8%, with a sensitivity of 93.2% and a precision specificity is 90.1%. The authors also tested their system on a small pneumonia dataset of approximately 5,000 images, achieving an average accuracy of 92.8%, sensitivity of 93.2%, and precision specificity of 90.1%. This system could eventually help speed up patient diagnosis and orientation, allowing for earlier treatment and higher cure rates. Vianna [23] also investigated how to use transfer learning to create a radiographic image classification system, which is a critical component of a computer-aided diagnostic system. The authors discovered that a fine-tuned transfer learning system with data augmentation effectively reduces overfitting and outperforms two other models: training from scratch and the learning model. Only the final recycling classification should be transferred.

Motivation and purpose

CNN has made an important contribution to the field of visual comprehension. Many imaging comprehension challenges feature DCNN-based approaches, including the biomedical challenge Computerized Medical Imaging and Computer Aided Intervention (MICCAI), the challenge. brain tumour segmentation (BRATS), the challenge of multimodal brain tumour segmentation [8], and the challenge of Imagenet classification.

The International Conference on Pattern Recognition (ICPR) challenges [11] and the ischemic stroke lesion segmentation (ISLES) challenges [9]. As a technique for understanding medical images, DCNN has emerged as a strong contender.

DCNN has been successfully used in many medical imaging applications, including detecting and classifying tumours as benign or malignant [12], detecting skin lesions [21], and detecting images. Photocoagulation tomography [22], colon cancer detection [14], , heart [10], breast [12], chest, eyes, and so on. DCNN-based models, such as CheXNet [15,16], used to classify 1 different breast condition outperform human experts on average. DCNN has also dominated COVID-19 detection with chest X-ray/CT scans. DCNN research is now a popular topic at major conferences.

In addition, special issues of reputable journals are published to solve problems using deep learning models. The large amount of DCNN literature available demonstrates their effectiveness and widespread use. However, different research communities are developing these applications at the same time, and the common results can be found in a variety of journals and conference proceedings.

A large number of deep learning surveys have recently been published. A review of common deep learning techniques [21] describes the application of to medical imaging, bioinformatics, and sensing. [2] provides a comprehensive review of deep learning techniques for segmenting brain MRI images. [18] presents a study of deep learning techniques for segmenting medical images, as well as their achievements and challenges in medical image segmentation on a general adversary network or on a specific application. There are no DCNN applications in early detection of COVID-19 or many other areas.

The survey included research articles on various applications of DCNN in medical image understanding. The survey articles were obtained from the websites of various journals. The survey also included arxiv, conference proceedings on various medical imaging challenges. These articles' references are also checked. DCNN" or "deep learning" or "complex neural networks" or terms related to understanding medical images were used as queries. To be considered, these terms must appear in the title or summary.

The goal of this survey is to provide a comprehensive overview of the applications and methodology of DCNN and its variants in medical imaging, including the development of the most recent global pandemic COVID-19. Summary tables are included in the survey for quick reference.

The authors use their personal experiences as well as DCNN fraternal studies to provide insight into various modern DCNN models, DCNN model design challenges, and insights. to provide an overview of current research trends in the field and to motivate physicians Imaging and healthcare professionals are well-versed in the use of DCNN in research and diagnosis.

Concepts related to Medical Image processing

- ## Medical Image understanding

Internal organs must be visualised using medical imaging to detect abnormalities in their anatomy or function. Medical imaging devices, such as X-ray, CT, MRI, PET, and ultrasound scanners, capture and display the anatomy or function of internal organs as images or videos. Images and video must be understood in order to accurately detect and diagnose functional abnormalities.

When an anomaly is discovered, its precise location, size, and shape must be determined.

Traditionally, trained physicians have performed these tasks based on their judgement and experience. These tasks are intended to be performed by smart medical systems using an intelligent understanding of medical imaging. Understanding medical images requires the classification, segmentation, detection, and localization of medical images.

- ## Medical Image Classification

Medical image classification entails identifying and labelling medical images from a fixed set. The task is to extract features from an image and label them using the extracted features.

- ## Medical Image Segmentation

Medical image segmentation aids in image understanding, feature extraction and identification, and quantitative assessment of lesions or other abnormalities. It provides useful information for pathology analysis, which aids in diagnosis and treatment planning. The goal of segmentation is to divide an image into closely related regions.

- ## Medical Image Localization

Pathology self-location in images is a critical step for automated acquisition planning and post-image analysis tasks such as segmentation and functional analysis. Predicting the object in an image, drawing a bounding box around the object, and labelling the object are all steps in the localization process..

- ## Medical Image detection

Image detection attempts to classify and localise regions of interest by drawing and labelling bounding boxes around areas of interest. This assists in determining the precise location and orientation of the various organs. It should aid people in receiving better treatment for a variety of symptoms.

Experimental design

Neural network of cathartic picture classification data

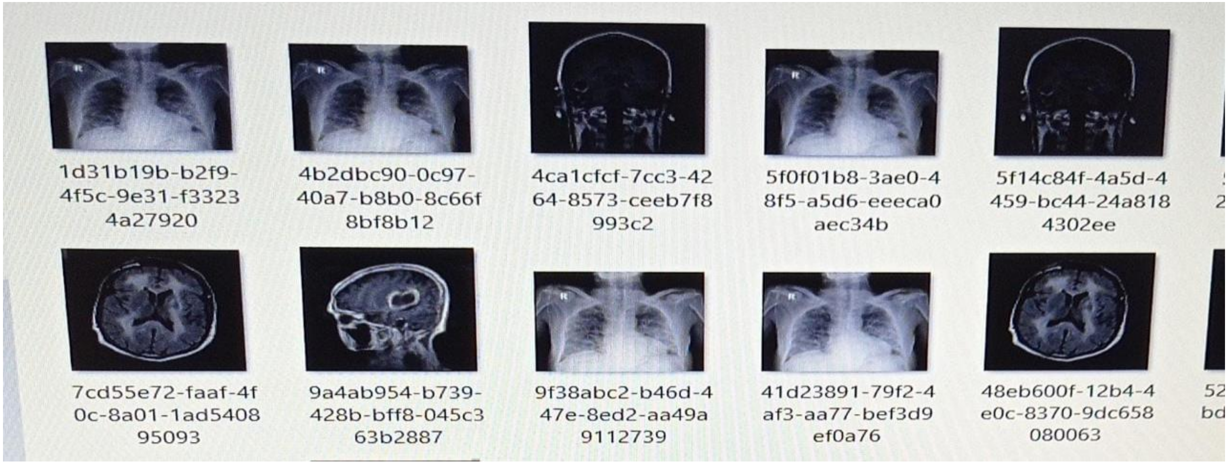

Fig 1.0 Dataset of Diseases

The dataset was created by Kermnay et al. [3]. It has two types of chest X-ray images: NORMAL and PNEUMONIA, which are kept in separate folders. File names in the PNEUMONIA directory distinguish two types of PNEUMONIA: bacteriophages and viruses.

There are 5232 x-ray images in the training dataset and 62 images in the test dataset. The image of the NORMAL layer accounts for only a quarter of the total data in the training dataset. PNEUMONIA covers 62.5% of the data in the test dataset, implying that the accuracy of the test data should be greater than 62.5%.

For starters, the new dataset is small and similar to the original. Overfitting is possible due to the small size of the data.In this case, use the DCNN code to train the linear classifier.

Second, the new dataset is large and comparable to the original. Because overfitting will not occur due to a lack of data, the entire network must be fine-tuned.

Third, while the new dataset is small, it differs significantly from the original data set. Because the learned data differs from the original data, the enable value in the network's front-end layer will be used to train the SVM. Fourth, the new data set is large and dissimilar to the original data set. CNN can be deployed immediately due to the large amount of data.

Main Applications of DCNN

DCNN applications are used across a wide range of industries. It is primarily used to solve a wide range of real-world issues, including image analysis, intelligent chatbots, robotics, data generation, natural language processing, and so on. Image recognition, speech recognition, video object tagging, sentiment analysis, flaw detection, self-driving cars, text summarization, and mobile image and video processing are all examples of machine learning applications. Some of the world's largest corporations, including NASA, Airbnb, Airbus, Uber, SAP, and IBM, use the TensorFlow software library. TensorFlow is used in several applications, including Dropbox, Snapchat, CEVA, and Twitter (Carneiro et al., 2017). These tools are widely available, whether publicly or privately, and are well-known not only in commercial organisations but also in academic communities.

DCNN Application in medical image Classification

COVID-19 is a worldwide pandemic disease that is rapidly spreading. The reverse transcription polymerase chain reaction is a popular test for detecting COVID-19 infection (RT-PCR). The gold standard for COVID-19 testing is RT-PCR testing; however, it is a complicated, time-consuming, and labor-intensive process with limited availability and accuracy. Because it is more accurate at diagnosis, a chest X-ray could be used for initial COVID-19 screening in areas where RT-PCR kits are scarce. Deep learning has been used by many researchers to determine whether a chest infection is caused by COVID-19 or another ailment.

DCNN CONCEPTS

- **DCNN Customized**

One of the first models proposed for COVID-19 detection was a simple pretrained AlexNet model proposed and fine tuned on chest X-ray images. The results looked promising, with an accuracy of around 95% in distinguishing between positive and negative patients. It was also suggested that pretrained ResNet and InceptionNet CNN models be used with transfer learning. With a test accuracy of 93%, these models demonstrated that transfer learning models were also efficient.

- **DCNN Fusion**

Combining two-dimensional DCNN and three-dimensional DCNN improves accuracy, as demonstrated by [19]. Three-dimensional DCNN was used to retain data along the Z axis, which is essential for brain image analysis. Because brain CT images are thicker than MRI images, CT images were geometrically normalised.

The output of the final conv layer of the two-dimensional DCNN was fused with three-dimensional convoluted data to produce three classes (Alzheimer's, lesions, and healthy data). In terms of accuracy, it outperformed the two hand-crafted approaches, SIFT and KAZE. The AD, lesion, and normal classes received 86.7 percent, 78.9 percent, and 95.6%, respectively.

- **The Small kernel**

[22] proposed DCNN Patch-wise training with small filter sizes for glioma segmentation. Deeper architecture was possible while retaining the same receptive fields. Two separate models were trained for high and low gliomas. Eight conv layers and three dense layers were present in the high glioma model. The low glioma model had four conv layers and three dense layers. Maxpooling was combined with dropout for dense layers. It finished fourth in the BRATS-2015 competition. Rotation was used to supplement data, which improved glioma segmentation performance.

- **Multipath DCNN**

[8] demonstrated that improving segmentation output requires two pathways, one for convolution and the other for deconvolution. The model was used to automatically segment MS lesions. A convolutional pathway with alternating conv and pool layers was included in the model, as was a deconvolutional pathway with an alternate deconv layer and an unpooling layer.

For pretraining, convolutional RBMs were used (convRBM). Pretraining and fine training were performed on a GPU-accelerated implementation of highly optimised three-dimensional convRBMs and convolutional encoder networks (CEN). It was compared to five publicly available methods and established as a comparison point. Model performance was evaluated using DSC, TPR, and FPR evaluation metrics.

Disorders of the brain

Alzheimer's disease causes memory loss by destroying brain cells. It has been difficult to classify Alzheimer's disease (AD) because it requires the selection of discriminative features.

Tumors of the brain

MRI is used to obtain detailed images of the brain in order to diagnose tumours. The extraction of high-level features makes automatic segmentation of a brain tumour extremely difficult.

Conclusion and future work

Any illness, whether treatable or not, must be accurately diagnosed and treated as soon as possible. As is frequently stated, the key to treating any disease is early detection. Because the body's natural defences decline with age, seniors are more vulnerable to illness, particularly pneumonia. This is a condition that, when compared to other ages, appears to have a completely different impact on the elderly. Pneumonia, brain tumours, and fever, one of the illnesses with the highest fatality rates worldwide, are the three most common causes of death in children today. It is a lung infection caused by bacteria, fungus, or viruses.Highly skilled doctors frequently review chest X-ray radiography to diagnose pneumonia.

Given the importance of medical imaging classification and the particular challenge of small medical image datasets, this article has chosen to investigate and evaluate how to apply CNN-based classification to the small chest radiograph dataset.

The following findings were presented as a result of the experiments. The best method among the three is CNN-based forward learning. ORB and SVM classifiers are outperformed by the capsule network. In general, CNN-based methods outperform traditional methods because they can automatically and efficiently learn and select features; your best results will come from transfer learning about VGG16 with recycled ConvLayer, steam superior to the result of the beginning of art. Specific functions can learn from new data sets when ConvLayer is not frozen.

As a result, specificity is a necessary component for improving accuracy; a balance between a model's expressive power and redundancy is required. A network that is too simple frequently cannot learn enough from the data and thus cannot achieve high accuracy. A very complex network, on the other hand, is difficult to train and tends to overflow quickly. As a result, the accuracy remains low. Only one network model with proper sizing and other effective redundancy prevention methods, such as consistent dropout rates and appropriate data increment, can achieve the best results.

However, due to time constraints, future research should be conducted: The formation of a Neural network with unfrozen ConvLayers tends to be overloaded in transfer learning. What are the most effective ways to stabilise the formation process? Other more powerful CNN models, such as ResNetv2 and a collection of several CNN models that have not been evaluated but have the potential to improve results; As these are critical, visualisation should be added to improve understanding and interpretation of CNN-based system results. to use a CNN-based system in real-world clinical settings.

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