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Detecting Diabetic Retinopathy in Retina Photos Blindness with Deep Learning Using CNNs

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Abstract: Diabetic retinopathy (DR) is one of the leading causes of vision loss. The World Health Organization reports that more than 300 million people worldwide have diabete. In 2019, the global prevalence of DR among individuals with diabetes was at more than 25%). The prevalence has been rising rapidly in developing countries. Early detection and treatment are crucial steps towards preventing DR. The screening procedure requires a trained clinical expert to examine the fundus photographs of the patient's retina. This creates delays in diagnosis and treatment. This is especially relevant for developing countries, which often lack qualified medical staff to perform the diagnosis.

Automated detection of DR can speed up the efficiency and coverage of the screening programs. Main purpose of image diagnosis is to identify abnormalities. Deep learning uses efficient method to do the diagnosis in state of the art manner. Applications of deep learning in healthcare industry provide solutions to variety of problems ranging from disease diagnostics to suggestions for personalized treatment. Various methods of radiological imaging have generated good amount of data but we are still short of valuable useful data at the disposal to be incorporated by deep learning model.

Keywords: CNN, Diabetic Retinopathy, Deep Learning, AI, ML.

1. INTRODUCTION

Medical imaging consists of set of processes or techniques to create visual representations of the interior parts of the body such as organs or tissues for clinical purposes to monitor health diagnose and treat diseases and injuries. Moreover, it also helps in creating database of anatomy and physiology [1].

Owing to the advancements in the field today medical imaging has the ability to achieve information of human body for many useful clinical applications. A different type of medical imaging technology gives different information about the area of the body to be studied or medically treated [2]. Organizations incorporating the medical imaging devices include freestanding radiology and pathology facilities as well as clinics and hospitals.

Major manufacturers of these medical imaging devices include Fujifilm, GE, Siemens Healthineers, Philips, Toshiba, Hitachi and Samsung. With the advancement and increase in the use of medical imaging [11], the global market for these manufactured devices for medical imaging is estimated to generate around $48.6 billion by 2025 which was estimated to be $34 billion in 2018 (Note: New York, NY, May 20, 2019 (GLOBE NEWSWIRE) -- Zion Market Research has published a new report titled “Medical Imaging Market by Product (Nuclear Imaging Equipment, Computed Tomography Scanners, X-Ray Devices, Ultrasound Systems, Digital Imaging[14], and Magnetic Resonance Imaging) and by Application (Diagnostics Center, Community Health Services, Hospitals, Research Institutes, Clinics, and Others): Global Industry Perspective, Comprehensive Analysis, and Forecast, 2018–2025” [5]. Bosubabu Sambana also proposed image scanning various levels[ ].According to the report, the global medical imaging market was approximately USD 34 billion in 2018 and is expected to generate around USD 48.6 billion by 2025, at a CAGR of around 5.2% between 2019 and 2025. The medical imaging technology is a part of biological imaging and uses various technologies, such as x-ray scan, MRI, CT-scan, etc., to diagnose diseases and help doctors/physicians decide the course of treatment [12].

Medical imaging is perceived to view and analyze the internal aspects of the body with various sets of techniques that non-invasively produce images. This technology is also used for follow-up sessions after the disease is diagnosed or treated [3]. The growing investments made by governments of emerging countries and technological advancements witnessed in medical imaging are expected to fuel the growth of the medical imaging market globally. Additionally, the increase in the awareness of early-stage detection of diseases and the rise

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in the aging population are also anticipated to fuel the global medical imaging market. However, the high costs of setup and machine may hinder the medical imaging market development [13].

Browse through 37 Tables & 27 Figures spread over 110 Pages and in-depth TOC on “Global Medical Imaging Market Size & Trends 2018 Report: Industry Share, Growth, CAGR, Segments, Analysis and Forecast to 2025”. Request Free Sample Report of Global Medical Imaging Market. On the basis of product, the medical imaging market includes magnetic resonance imaging, nuclear computed tomography scanners, imaging equipment, ultrasound systems, x-ray devices, and digital imaging. In 2018, x-ray devices contributed almost 27.5% of the total revenue generated by the medical imaging market globally [5].

The x-ray devices segment is expected to lead the global market in the future, due to their ubiquitous usage and assistance in the diagnosis of various diseases. Increase in the prevalence of orthopedic injuries and accidents, less exposure to radiation, and higher quality of images have also fueled the growth of x-ray devices [15]. The nuclear imaging equipment segment is expected to show fast growth in the years ahead, due to the on-going developments witnessed in new radiotracers and the rising prevalence of cancer and cardiovascular diseases. The application segment includes diagnostics center, community health services, hospitals, research institutes, clinics, and others [6].

Hospitals have a large patient pool that is suffering from various chronic diseases. For the diagnosis and treatment of these diseases, hospitals have a greater number of medical imaging technologies as compared to their counterparts. Thus, the hospitals are expected to dominate the global market in the upcoming years.

Why is it so important?

The use of medical imaging for diagnostic services is regarded as a significant confirmation of assessment and documentation of many diseases and ailments. High quality imaging improves medical decision making and can reduce unnecessary medical procedures. For example, surgical interventions can be avoided if medical imaging technology like ultrasound and MRI are available.

Earlier diagnosis included exploratory procedures to figure out issues of ageing person, children with chronic pain, detection of early diabetes and cancer. With the advent of medical imaging the vital information of health can be made available from time to time easily which can help diagnose illnesses like pneumonia, cancer, internal bleeding, brain injuries, and many more. Medical imaging is an ever-changing technology [10]. With the advancement in the field of computer vision the medical imaging is improving day by day. This means that the benefits of it will keep on improving in coming time as more and more computer vision researchers and medical professionals are coming together for the advancement of medical imaging [8].

2. BACKGROUND

Diabetic retinopathy (DR) is one of the leading causes of vision loss. The World Health Organization reports that more than 300 million people worldwide have diabetes (Wong et al. 2016). In 2019, the global prevalence of DR among individuals with diabetes was at more than 25% (Thomas et al. 2019). The prevalence has been rising rapidly in developing countries.

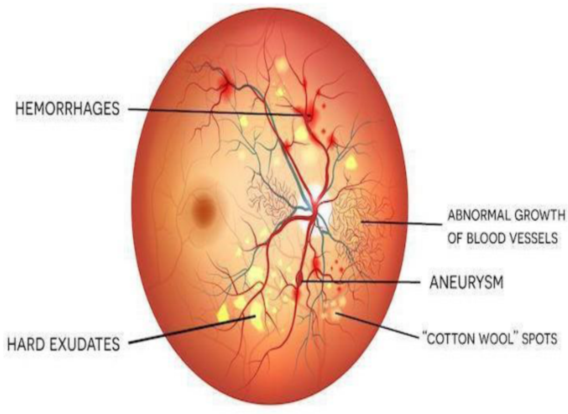


Figure.1: Diabetic retinopathy

Early detection and treatment are crucial steps towards preventing DR. The screening procedure requires a trained clinical expert to examine the fundus photographs of the patient's retina. This creates delays in diagnosis and treatment [14]. This is especially relevant for developing countries, which often lack qualified medical staff to perform the diagnosis.

Automated detection of DR can speed up the efficiency and coverage of the screeningprograms [9].

Data Preparation

Data preparation is a very important step that is frequently underestimated. The quality of the input data has a strong impact on the resulting performance of the developed machine learning models. Therefore, it is crucial to take some time to look at the data and think about possible issues that should be addressed before moving on to the modeling stage [14].

Data exploration

The images are labeled by a clinical expert. The integer labels indicate the severity of DR on a scale from 0 to 4, where 0 indicates no disease and 5 is the proliferative stage of DR. Let's start by importing the data and looking at the class distribution. The data is imbalanced: 49% images are from healthy patients. The remaining 51% are different stages of DR. The least common class is 3 (severe stage) with only 5% of the total examples.

The data is collected from multiple clinics using a variety of camera models, which creates discrepancies in the image resolution, aspect ratio and other parameters. This is demonstrated in the snippet below, where we plot histograms of image width, height and aspect ratio [11]. Now, let's look into the actual eyes! The code below creates the EyeData dataset class to import images. We also create a DataLoader object to load sample images and visualize the first batch.

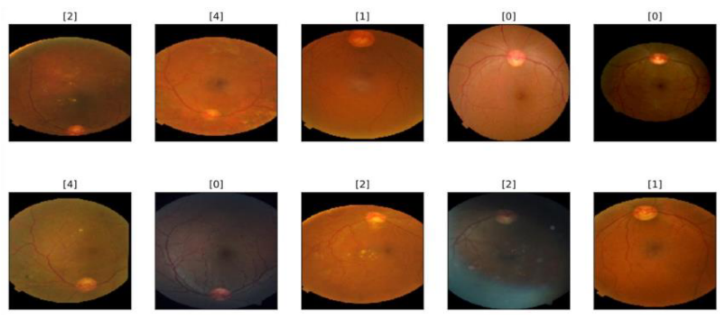


Figure.2: The illustration further emphasizes differences in the aspect ratio and lighting conditions.

The severity of DR is diagnosed by the presence of visual cues such as abnormal blood vessels, hard exudates and so-called cotton wool spots [12]. You can read more about the diagnosing process here. Comparing the sample images, we can see the presence of exudates and cotton wool spots on some of the retina images of sick patients [8].

Image preprocessing

To simplify the classification task for our model, we need to ensure that retina images look similar.

First, using cameras with different aspect ratios results in some images having large black areas around the eye. The black areas do not contain information relevant for prediction and can be cropped. However, the size of black areas varies from one image to another. To address this, we develop a cropping function that converts the image to grayscale and marks black areas based on the pixel intensity [5]. Next, we find a mask of the image by selecting rows and columns in which all pixels exceed the intensity threshold. This helps to remove vertical or horizontal rectangles filled with black similar to the ones observed in the upper-right image. After removing the black stripes, we resize the images to the same height and width.

Another issue is the eye shape. Depending on the image parameters, some eyes have a circular form, whereas others look like ovals. Since the size and shape of cues located in the retina determine the disease severity, it is crucial to standardize the eye shape as well [8]. To do so, we develop another function that makes a circular crop around the center of the image.

Finally, we correct for the lightning and brightness discrepancies by smoothing the images using a Gaussian filter. The snippet below provides the updated prepare_image() function that incorporates the discussed preprocessing steps.

Modeling

CNNs achieve state-of-the-art performance in computer vision tasks. Recent medical research also shows a high potential of CNNs in DR classification (Gulshan et al. 2016).

In this paper, we employ a CNN model with the Efficient Net architecture. Efficient Net is one of the recent state-of-the-art image classification models (Tan et al. 2019). It encompasses 8 architecture variants (B0 to B7) that differ in the model complexity and default image size [9].

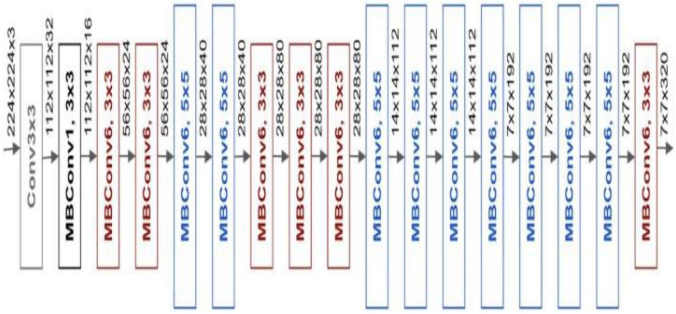
The architecture of EfficientNet B0 is visualized below. We test multiple EfficientNet architectures and use the one that demonstrates the best performance [13].

The modeling pipeline consists of three stages:

Pre-training. The data set has a limited number of images (N = 3,662). We pre-train the CNN model on a larger data set from the previous Kaggle competition.

Fine-tuning: We fine-tune the model on the target data set. We use cross-validation and make modeling decisions based on the performance of the out-of-fold predictions.

Inference. We aggregate predictions of the models trained on different combinations of training folds and use test-time augmentation to further improve the performance.



Pre-training

Due to small sample size, we cannot train a complex neural architecture from scratch. This is where transfer learning comes in handy. The idea of transfer learning is to pre-train a model on a different data (source domain) and fine-tune it on a relevant data set (target domain).

A good candidate for the source domain is the ImageNet database. Most published CNN models are trained on that data. However, ImageNet images are substantially different from the retina images we want to classify. Although initializing CNN with ImageNet weights might help the network to transfer the knowledge of basic image patterns such as shapes and edges, we still need to learn a lot from the target domain [14].

Different kinds and their corresponding approaches

Medical imaging is a part of biological imaging and incorporates radiology which includes following technologies:

Radiography: One of the first imaging techniques used in modern medicine. It uses wide beam of X-rays to view non-uniformly composed material. These images help in assessment of the presence or absence of disease, damage or foreign object.

Two forms of radiographic images are used in medical imaging which are:

a) **Fluoroscopy:** Produces real-time internal body part images but requires constant input of lower dose rate of X-rays. Thus, mainly used in image-guiding procedures where continuous feedback is demanded by the procedure.

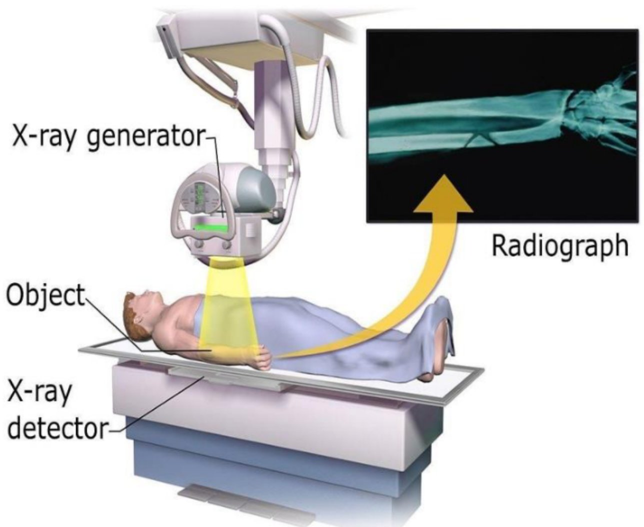


Figure. 3: Projectional Radiography

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b) **Projection Radiography:** More commonly used form of X-rays to determine the type and extent of the fracture and pathological changes in the lung. They are used to visualize internal areas around stomach and intestine and therefore, can help in diagnosing ulcers and certain type of colon cancer.

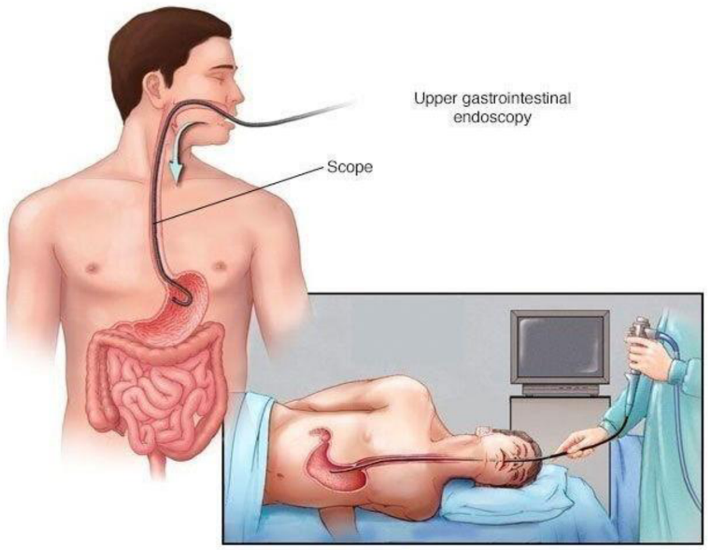
MRI - Magnetic Resonance Imaging: MRI scanner uses powerful magnets thereby emitting radio frequency pulse at the resonant frequency pulse of the hydrogen atoms to polarise and excite hydrogen nuclei of water molecules in human tissue. MRI doesn't involve X-rays nor ionizing radiation.

MRI is widely used in hospitals and seen as a better choice than a CT scan since MRI helps in medical diagnosis without exposing body to radiation [12]. MRI scans take longer time and are louder. Moreover, people with medical implants or non- removable metal inside body can't undergo MRI scan safely.

Ultrasound : Ultrasound uses high frequency broadband MH range sound waves that are reflected by tissue to varying degrees to produce sort of 3D images. It is most commonly associated with foetus imaging in a pregnant woman. Ultrasound is also used for the imaging of abdominal organs, heart, breast, muscles, tendons, arteries and veins.

It provides less anatomical detail relative to CT or MRI scans. Major advantage is ultrasound imaging helps to study the function of moving structures in real-time without emitting any ionising radiation. Very safe to use, can be quickly performed without any adverse effects and relatively inexpensive [10-13].

Endoscopy: Endoscopy uses an endoscope which is inserted directly into the organ to examine the hollow organ or cavity of the body. The type of endoscope differs depending upon the site to be examined in the body and can be performed by a doctor or a surgeon [14]. Endoscopy is used to examine gastrointestinal tract, respiratory tract, ear, urinary tract, etc. Main risks involved with this procedure are infection, over-sedation, perforation, tear lining and bleeding.



Thermography : Thermo graphic cameras detect long infrared radiations emitted by the body which create thermal images based on the radiations received. The amount of radiation increases with increase in temperature. Therefore, thermography helps in checking variations in temperature. It is capable of capturing moving objects in real time. Thermographic cameras are quite expensive. Images of the objects having varying temperatures might not result into accurate thermal imaging of itself [15].

Nuclear Medicine Imaging: This type of medical imaging is done by taking radio- pharmaceuticals internally. Then, external gamma detectors capture and form images of the radiations which are emitted by the radio-pharmaceuticals. This is opposite of X-rays where radiations are through the body from outside but in this case the gamma rays are emitted from inside the body. However, the radiation dosages are small still there's a potential risk [6].

Tomography: Single photon emission computed tomography (SPECT) also known as tomography uses gamma rays for medical imaging. The gamma emitting radioisotope is injected in the bloodstream. SPECT is used for any gamma imaging study which is helpful in treatment especially for tumors, leukocytes, thyroids and bones. We have discussed the important ones above but there are many more medical imaging techniques helping and providing solutions during various medical cases.

Techniques such as ElectroEncephalogy (EEG), magnetoencephalogy (MEG), electrocardiography (ECG) which produces data in form of graph with respect to time contain important information of the human body part but can't be considered as a part of medical imaging directly.

Deep Learning for Healthcare

Main purpose of image diagnosis is to identify abnormalities. Deep learning uses efficient method to do the diagnosis in state of the art manner. Applications of deep learning in healthcare industry provide solutions to variety of problems ranging from disease diagnostics to suggestions for personalized treatment [9].

Various methods of radiological imaging have generated good amount of data but we are still short of valuable useful data at the disposal to be incorporated by deep learning model. Let's discuss some of the medical imaging breakthroughs achieved using deep learning:

Diabetic Retinopathy

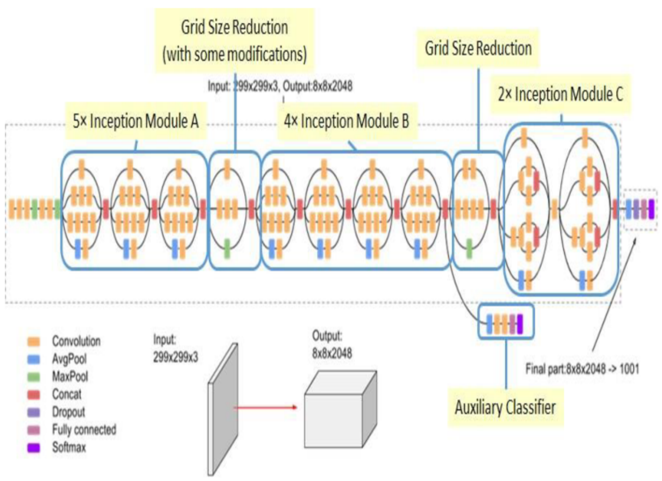
There are two types of disorders owing to diabetes. Diabetes Mellitus being the metabolic disorder where Type-1 being the case in which pancreas can't produce insulin and Type-2 in which the body don't respond to the insulin, both of which lead to high blood sugar. Diabetic Retinopathy is an eye disorder owing to diabetes resulting in permanent blindness with the severity of the diabetic stage.

According to World Health Organisation (WHO)

- The numbers of people suffering from diabetes have increased from 108 millions in 1980 to 422 millions in 2014.
- The disease is increasing in low and medium income countries.
- Diabetes is the major cause of blindness, kidney failure, heart attacks, stroke and lower limb amputation.
- In 2016, approximately 1.6 million deaths were due to diabetes and this approximation is estimated to raise upto 2.2 million for the year 2022 due to high blood glucose levels.
- Diabetic retinopathy is an important cause of blindness, and occurs as a result of long-term accumulated damage to the small blood vessels in the retina. 2.6% of global blindness can be attributed to diabetes.
- Diabetic retinopathy can be controlled and cured if diagnosed at an early stage by retinal screening test. Manual processes to detect diabetic retinopathy is time consuming owing to equipment unavailability and

expertise required for the test. Issue being the disease doesn't show any symptoms at early stage owing to which ophthalmologists need a good amount of time to analyses the fundus images which in turn cause delay in treatment [12].

- Deep learning based automated detection of diabetic retinopathy has shown promising results. Gulshan et al. research where they applied Deep Convolutional Neural Network (DCNN) on the following two datasets for the classification between moderate and worse Referable Diabetic Retinopathy (RDR): Eye Picture Archive Communication System (EyePACS-1) dataset : 9963 images from 4997 patients and the Messidor-2 dataset : 1748 images from 874 patients. The algorithm devised by Gushan et al. claimed to have achieved 97.5% sensitivity and 93.4% specificity on EyePACS-1 data, and 96.1% sensitivity and 93.9% specificity on Messidor-1. The specific neural network used in this work is the Inception-v3 architecture proposed by Szegedy et al.



Google AI team worked closely with doctors both in India and US to create a dataset of 128,000. Each of which were evaluated by 3-7 ophthalmologists from a panel of 54 ophthalmologists. This dataset was used to train a deep neural network to detect RDR. Algorithm's performance was further tested on two separate validation sets (totalling approx. 12000 images), with the decision of a panel of 7 or 8 U.S. board certified ophthalmologists serving as reference standard.

The performance was mind blowing and matched that of the ophthalmologists. On validation set the algorithm performed with F1-score of 0.95, better than the median F1-score of the 8 ophthalmologists (measured at 0.91) whom were consulted for the research.

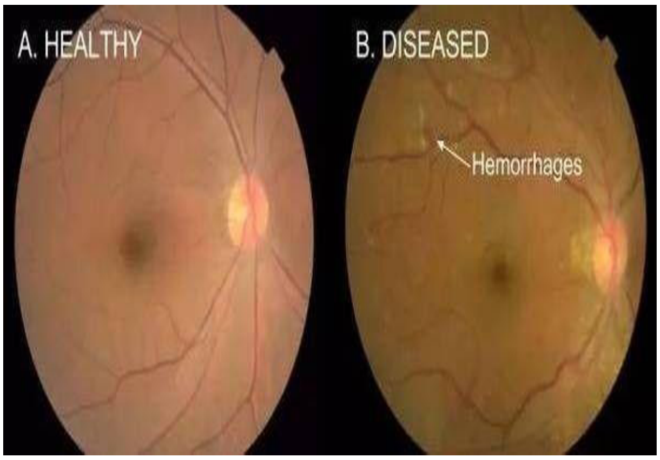
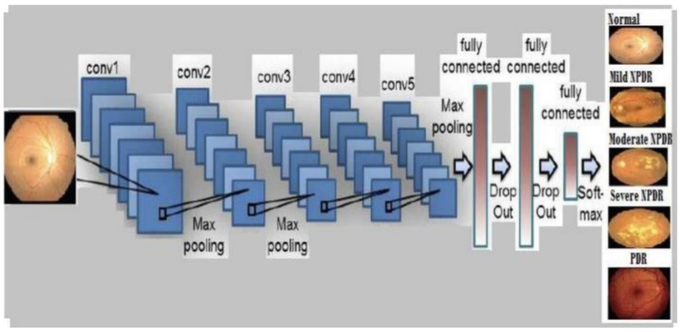


Figure.4: Examples of retinal fundus photographs that are taken to screen for DR. The image on the left is of a healthy retina (A), whereas the image on the right is a retina with referable diabetic retinopathy (B) due a number of haemorrhages (red spots) present.

Kathirvel et al trained a DCNN with dropouts on publicly available Kaggle, DRIVE and STARE dataset to classify affected and healthy fundus which reported accuracy of 94%. Kaggle dataset include clinician labelled image across 5 classes namely : No DR, Mild, Moderate, Severe and Proliferative DR.

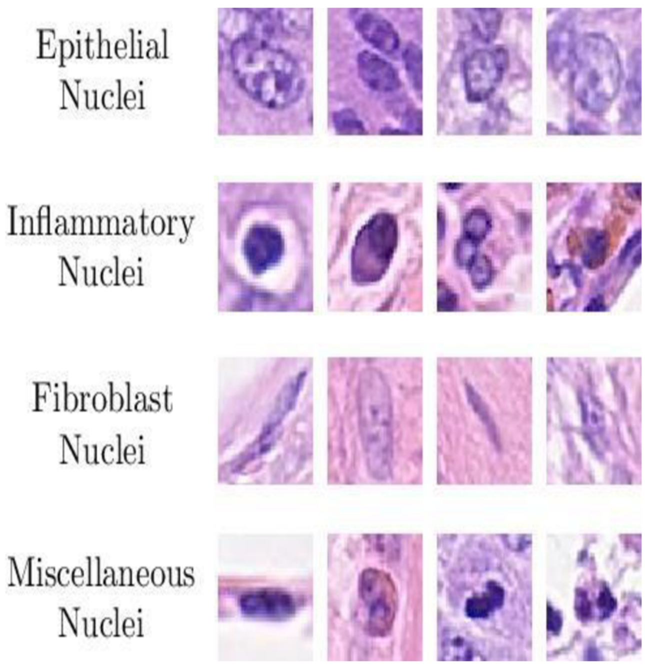


With the advancements in the methods of automated diabetic retinopathy screening methods with high metrics pose a strong potential to assist doctors in evaluating more patients and speed up the diagnostic process which in turn can reduce the time gap for treatments [12][14]. Google is trying hard to work with doctors and researchers to streamline the screening process across the world with hope that these methods can benefit maximally to both patients as well as doctors [7]. Moreover working with the FDA and other regulatory agencies to further evaluate these technologies in clinical studies to make this as a standard part of the procedure.

Histological and Microscopial Elements Detection

Histological analysis is the study of cell, group of cells and tissues. Microscopic imaging technology and stains are used to detect the microscopic changes occurring at cellular and tissue level. It involves steps which include fixation, sectioning, staining and optical microscopic imaging [8].

Microscopial imaging is used for diseases like squamus cell carcinoma, melanoma, gastric carcinoma, gastric ephithilial metaplasia, breast carcinoma, malaria, intestinal parasites, etc. Genus plasmodium parasite are the main cause of malaria and microscopial imaging is the standard method for parasite detection in blood smear samples. Mycobacteria in sputum is the main cause of Tuberculosis. Smear microscopy and fluroscent auramine-rhodamin stain or Ziehl-Neelsen stain are standard methods for Tuberculosis diagnosis.



- In 2016, Department of Computer Science of University of Warwick opened the CRCHistoPhenotypes - Labeled Cell Nuclei Data. The data includes 100 H&E stained histology images of colorectal adenocarcinomas.
- Out of which a total of 29,756 nuclei were labelled for detection and 24,444 nuclei among them had class labels associated with them.

These class labels were epithelial, inflammatory, fibroblast and miscellaneous.

Example patches of different types of nuclei found in the dataset used by Sirinukunwattana et al, 1st Row - Epithelial nuclei, 2nd Row - Inflammatory nuclei (from left to right, lymphocyte, plasma nucleus, neutrophil, and eosinophil), 3rd Row - Fibroblasts, 4th Row - Miscellaneous nuclei (from left to right, adipocyte, endothelial nucleus, mitotic figure, and necrotic nucleus).

Bayramoglu et al aimed at the issue of limited availability of training data. This research checks the possibility of using transfer learning to minimise the hurdle owing to less data and still obtain a good hidden representation with limited data availability.

Quinn et al research employed a setup to capture blood smear images, sputum samples images and stool samples images. The experts identified bounding boxes around each object of interest in every image [16]. In thick blood smear images, plasmodium were annotated (7245 objects in 1182 images); in sputum samples, tuberculosis bacilli were annotated (3734 objects in 928 images), and in stool samples, the eggs of hookworm, Taenia and Hymenolepsis nana were annotated (162 objects in 1217 images).

Automatic microscopic diagnostic analysis was done by training [5] Deep Convolutional Neural Networks (DCNNs) separately for each which resulted in high AUC of 1.00 for plasmodium images to detect Malaria, 0.99 for tuberculosis bacilli and 0.99 for hookworm detection.

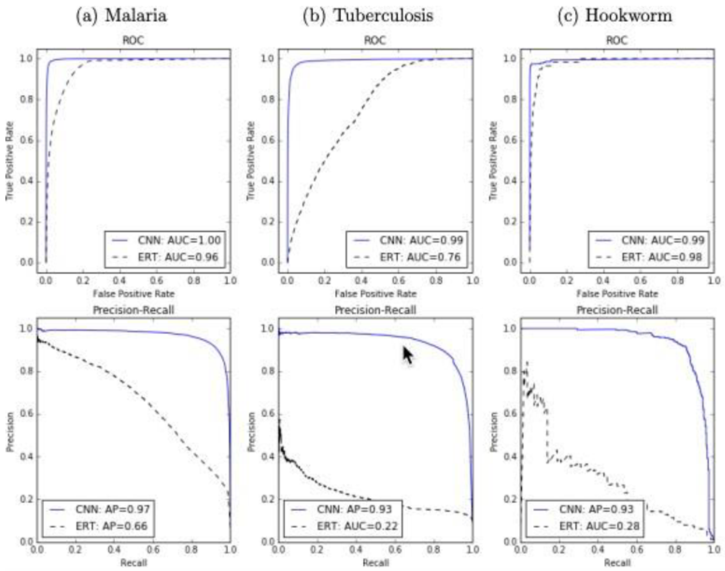
In this work, DCNN used comprised of four hidden layers:

a) Convolution layer: 7 filters of size 3×3.
b) Pooling layer: max-pooling, factor 2.
c) Convolution layer: 12 filters of size 2×2.
d) Fully connected layer, with 500 hidden units.

ROC and precision-recall for malaria, tuberculosis and intestinal parasites detection, showing Area under Curve (AUC) and Average Precision (AP).

Malaria detection is highly crucial and important. According to 2018 reports by World Health Organization (WHO), in 2018, an estimated 228 million cases of malaria occurred worldwide out of which there were an estimated 405,000 deaths from malaria globally [4].

Children aged less than 5 years are the most vulnerable group affected by malaria. In 2018, they accounted for 67% (272,000) of all malaria deaths worldwide.



Gastrointestinal Diseases Detection

Gastroinstestinal tract consists of all the organs which are involved in digestion of food and nutrient absorption from them starting from mouth to anus. The organs included are oesophagus, stomach, duodendum, large intestine(colon) and small intestine(small bowel). Oesophagus, stomach and duodendum constitute the upper gastrointestinal tract while large and small intestine form the lower gastrointestinal tract [9].

The digestion and absorption gets affected by the disorders like inflammation, bleeding, infections and cancer in the gastrointestinal tract. Ulcers cause bleeding in the upper gastrointestinal tract [8][11]. Polyps, cancer or diverticulitis cause bleeding from large intestine. Celiac, Crohn, tumors, ulcers and bleeding owing to abnormal blood vessels are the issues concerned with small intestine.

Current imaging technologies play vital role in diagnosing these disorders concerned with the gastrointestinal tract which include endoscopy, enteroscopy, wireless capsule endoscopy, tomography and MRI.

- Jia et al trained a DCNN to detect bleeding in wireless capsule endoscopy(WCE) images. The domain of computer aided diagnosis for gastrointestinal bleeding detection is an active area of research. Traditional methods were based on handcrafted features which are insufficient for blood detection with higher accuracy owing to very less capture of features.
- Therefore, deep convolutional neural network was applied on an expanded dataset of 10,000 WCE images. With the resultant F1-score of 0.9955 the DCNN based method outperformed the state-of-the-art approaches in WCE bleeding detection.

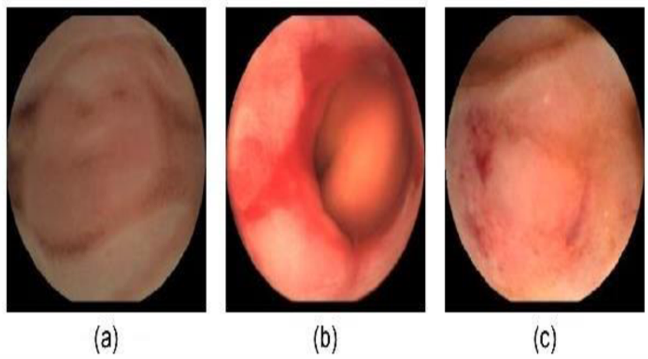


Figure.5: Examples of WCE images in our dataset. (a) A normal WCE image. (b) An active bleeding WCE image (c) An inactive bleeding WCE image.

Panpeng et al employs DCNN to detect intestinal haemorrhage in WCE images. WCE can painlessly capture a large number of internal intestinal images. However, only a small portion of these WCE images contain haemorrhage. Therefore, in order to to perform automated detection of intestinal haemorrhage data augmentation methods were employed to create a balanced dataset. As a result, the DCNN model achieved an F1-score of 0.9887.

Leenhardt et al employed DCNN to detect gastrointestinal angiectasia(GIA) in small bowel capsule endoscopy(SBCE) images of small intestine. GIA is the most common small intestinal vascular lesion with an inherent risk of bleeding [10]. SBCE is the currently accepted procedure. Still frames of SBCE were annotated with typical GIA and normal which were given to a DCNN to do semantic segmentation and classification. The algorithm devised received a sensitivity of 100% and specificity of 96%. The success of this deep learning based approach paved the way for the future development of softwares for automated detection of GIA from SBCE images [12].

- Urban et al employed DCNN to localise and detect polyps in screening colonoscopies. Colonoscopy is

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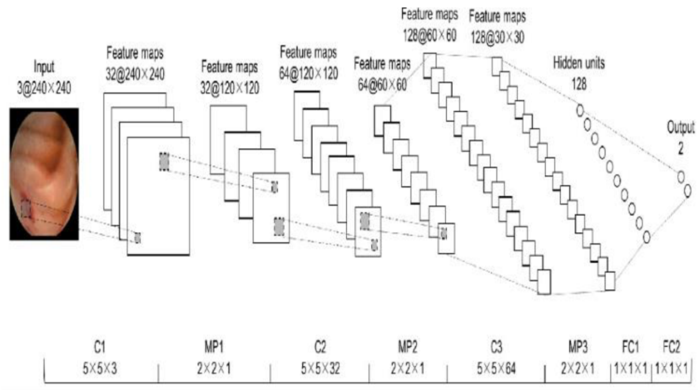
done for colorectal cancer prevention depends on the adenoma detection rate (ADR).



- The ADR by colonoscopists vary from 7% to 53%. It is estimated that with 1% increase in ADR risk of interval colorectal cancers decreases by 3%-6%.

- To develop new methods to increase the ADR a DCNN was trained on diverse and representative set containing 8,641 images from screening colonoscopies of more than 2000 patients labelled by expert colonoscopists.

- The resulted algorithm gave a AUC of 0.991 and an accuracy of 96.4%. This success has given hope to create an automated diagnostic system to increase the ADR to decrease interval colorectal cancers but requires validation in large multicenter trials.

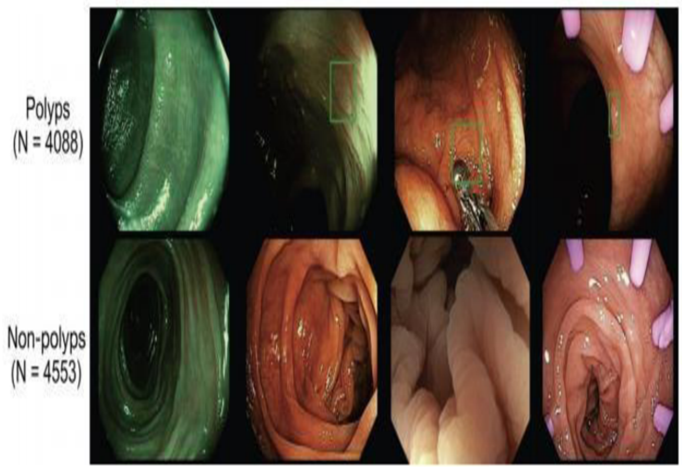


Figure. 6 : Examples of dataset used by Urban et al. (Top row) Images containing a polyp with a superimposed bounding box. (Bottom row) Nonpolyp images. Three pictures on the left were taken using NBI and 3 pictures on the right include tools (eg, biopsy forceps, cuff devices, etc) that are commonly used in screening colonoscopy procedures.

Cardiac Imaging

CT and MRI scans are the most widely used technology for cardiac imaging. The uphill task being the manual identification of the coronary artery calcium (CAC) scoring in cardiac CT scans which incorporates a good amount of effort. Therefore, making it to be a time consuming task for epidemiological studies.

Litjens et al research paper discusses different deep learning frameworks which can be used for different ways in cardiovascular analysis which has been shown in the diagrammatic representation below.

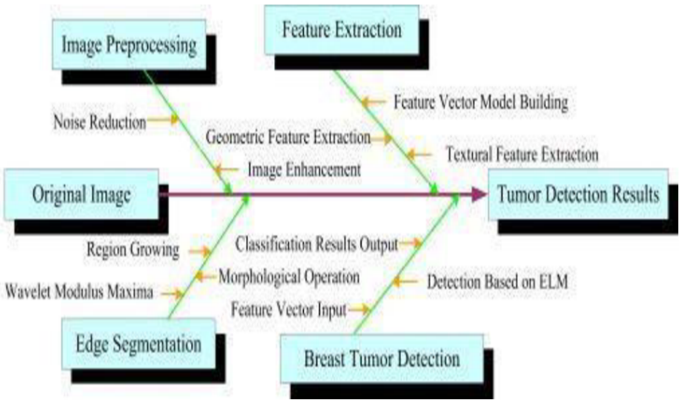
This flowchart highlights how certain applications can be realized by using a specific algorithm. The arrows indicate for which application an algorithm is typically used. Note that this does not mean that, for example, a fully-connected network cannot be used for segmentation, but it is not the most appropriate choice [9].

Tumor Detection

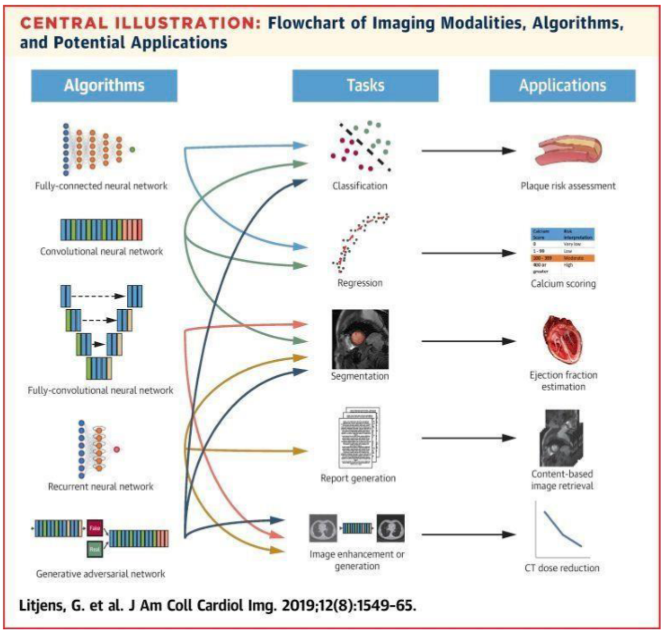
Abnormal growth of cells of any body part creating a separate mass of tissue. This is called tumor or neoplasm. Generally, cells in our body undergo a cycle of developing, ageing, dying and finally replaced by new cells. This cycle gets disrupted in case of tumor and other forms of cancer. There are two types of tumor : Benign (non-cancerous) and Malignant (cancerous). Benign tumors are not that dangerous and stick to one part of the body and do not spread to other parts. On the other hand, malignant tumor is extremely harmful spreading to other body parts. Spreading of malignant tumor makes both treatment and prognosis difficult [16].

Wang et al is one of the initial researches to detect breast cancer in digital mammography using machine learning. They used 482 mammographic images out of which 246 had tumors. Their patients were women from North-East China between the ages of 32 and 74.

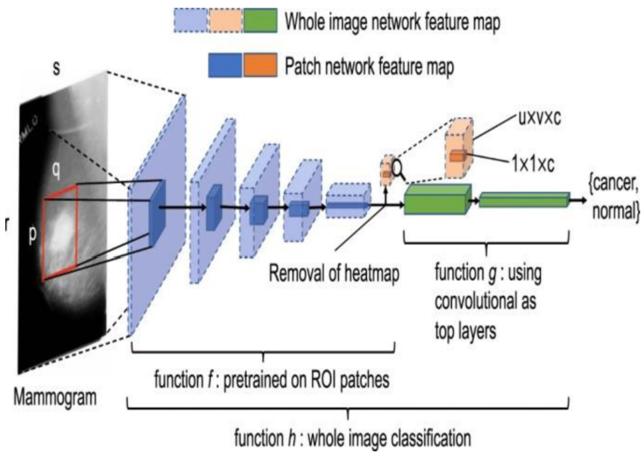
This image database was built using senographe 2000D full digital breast X-ray camera and confirmed by radiologists at Tumor Hospital of Liao Ning Province. The machine learning approaches involved two models one being the single layered neural network which was named extreme machine learning (ELM) and second being the traditional support vector machine (SVM). The images underwent through series of preprocessing techniques like noise reduction, edge enhancement, edge segmentation which was followed by geometrical and textural feature extraction [16].



These features were fed into the model and trained via cross validation approach. The results obtained had 84 error responses for ELM and 96 error responses for SVM out of 482 images [8]. This research done in 2012 didn't use CNN based approach but paved the way for the idea to use deep learning to do automated breast cancer detection in digital mammography.

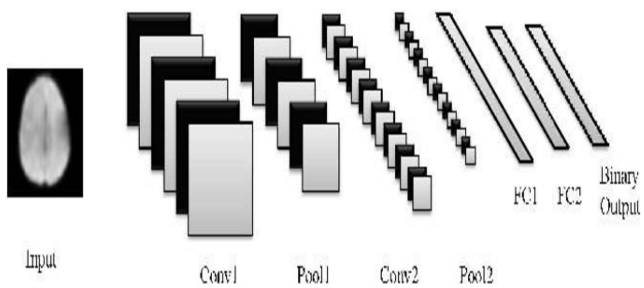


The training data was further split 90:10 to create a validation set. The splits maintained similar proportion of cancer cases in all the training, validation and test sets. The total numbers of images in the training, validation and testing sets were 1903, 199 and 376, respectively. Two patch datasets were created by sampling image patches from ROIs and background regions. All patches had the same size of 224 × 224, which were large enough to cover most of the ROIs annotated. The first dataset (S1) consisted of sets of patches in which one was centred on the ROI and one is a random background patch from the same image. The second dataset (S10) consisted of 10 patches randomly sampled from around each ROI, with a minimum overlapping ratio of



0.9 with the ROI and inclusion of some background, to more completely capture the potentially informative region; and an equal number of background patches from the same image [8]. All patches were classified into one of the five categories: background, malignant mass, benign mass, malignant calcification and benign calcification. The training consisted of two steps. The first step being to train the patch classifier to detect the region of interest (ROI) from the background using a DCNN.

The second step included to train an image classifier which would run on the ROI images obtained from first step [16]. The second step classifies the ROI image into one of the five categories which are background, malignant mass, benign mass, malignant calcification and benign calcification.



The training for the step two was done using Resnet-50 and VGG-16, confusion matrix of the results of which are shown in the figure below. Architecture used by Shen et al. converting a patch classifier to an end-to-end trainable whole image classifier using an all convolutional design. The function f was first trained on patches and then refined on whole images [16].

Confusion matrix analysis of 5-class patch classification for Resnet50 (a) and VGG16 (b) in the S10 test set. The matrices are normalized so that each row sums to one.

Alzheimer's and Parkinson's Detection

Alzheimer's Disease (AD) is brain disorder which is irreversible and slow progresses to destroy memory and thinking skills hampering the ability to carry out simple tasks. Accurate diagnosis of AD plays an important role for patients care particularly in the early phase of the disease.

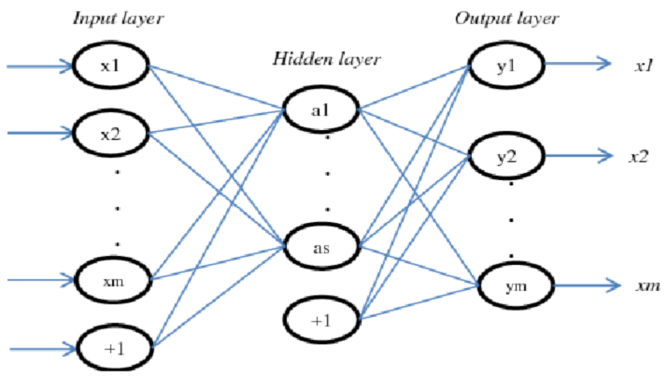


Figure. 7: Structure of an Autoencoder

Parkinson's disease is a neurological disorder causing progressing decline in motor system due to the disorder of basal ganglia in brain. The symptoms start with tremors in hand followed by slow movement, stiffness and loss in balance.

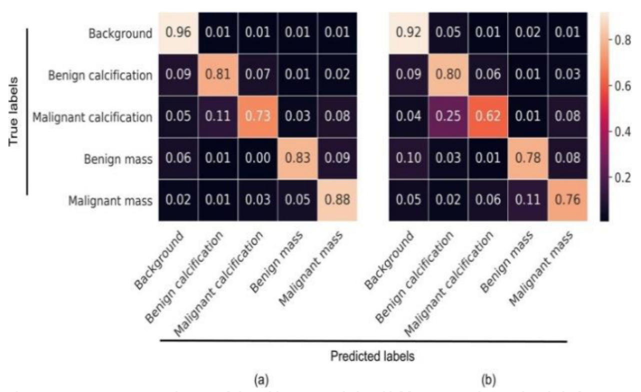


Figure.8: Examples of isolines with different threshold for a NC subject (A) and PD patient (B) Current Scenario and Challenges

Deep learning implementation in medical imaging makes it more disruptive technology in the field of radiology. Medical fields which have shown promises to be revolutionized using deep learning are:

- Ophthalmology
- Pathology
- Cancer diagnosis

Google DeepMind Health and National Health Service, UK have signed an agreement to process the medical data of 1 million patients.

IBM Watson has entered the imaging domain after their successful acquisition of Merge Healthcare.

Application of deep learning algorithms to medical imaging is fascinating and disruptive but there are many challenges pulling down the progress. Some of the major challenges are as follows:

Limited Datasets

The first and the major prerequisite to use deep learning is massive amount of training dataset as the quality and evaluation of deep learning based classifier relies heavily on quality and amount of the data. Limited availability of medical imaging data is the biggest challenge for the success of deep learning in medical imaging [8][17].

Development of massive training dataset is itself a laborious time consuming task which requires extensive time from medical experts[8][11]. Therefore, more qualified experts are needed to create quality data at massive scale, especially for rare diseases. Moreover, a balanced dataset is necessary for deep learning algorithms to learn the underground representations appropriately. In healthcare majority of the available dataset is unbalanced leading to class imbalance [16].

Privacy and Legal Issues

Sharing of medical data is severely complex and difficult compared to other datasets. Data privacy is both sociological as well as a technical issue, which needs to be addressed from both angles [17].

HIPAA (Health Insurance Portability and Accountability Act of 1996) provides legal rights to patients to protect their medical records, personal and other health related information provided to hospitals, health plans, doctors and other healthcare providers [11].

Therefore, with the increase in healthcare data anonymity of the patient information is a big challenge for data science researchers because discarding the core personal information makes the mapping of the data severely complex but still a data expert hacker can map through combination of data associations[8][17].

Differential privacy approaches can be undertaken which restricts the data to organization on requirement basis. Sharing of sensitive data with limited disclosure is a real challenge [15].

Therefore, it leads to a lot of restrictions. Limited data access owing to restriction reduces the amount of valuable information. Apart from that, the data is increasing day by day adding incremental threat to data security.

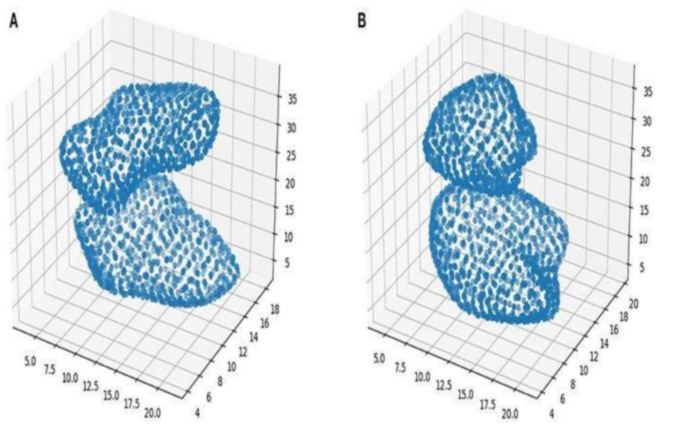


Figure. 9: Examples of is surfaces with threshold = 0.5 for a NC subject (A) and PD patient (B)

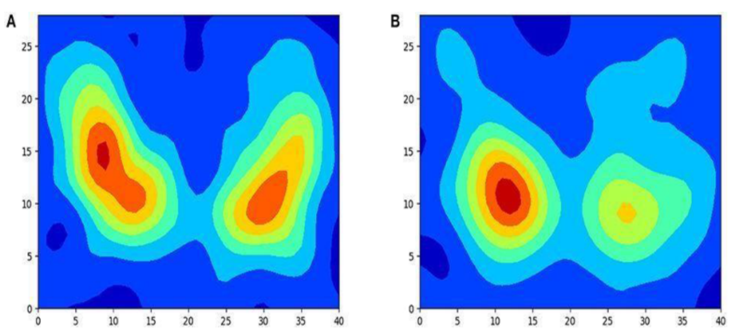


Figure.10:Examples of isolines with different threshold for a NC subject (A) and PD patient (B)

Detecting Diabetic Retinopathy with Deep Learning

Here, in this section we will create a binary classifier to detect diabetic retinopathy symptoms from the retinal fundus images. The data has been taken from the Kaggle Diabetic Retinopathy repository.

Kaggle dataset include 35000 clinician labelled image across 5 classes namely:

a) No DR
b) Mild
c) Moderate
d) Severe
e) Proliferative DR

Our objective here is to create a binary classifier to predict no DR or DR and not multi class classifier for 5 given classes. Therefore, we take the No DR data as no symptom class label and Severe as well as Proliferative DR as the as symptom class label [16].

The training dataset has 5 files out of which train001, train002, train003 and train004 were used for training and train005 data was used for validation. Considering the constraints of the huge dataset and RAM and GPU resources available I tried to devise this basic approach of feasible preprocessing steps and neural network model to create the above suggested binary classifier which includes.

Preprocessing included the following steps:

a) Image read and resizing to 512 x 512 x 3.
b) Green channel selection resulting the tensor to be of shape 512 x 512 x 1.

Moreover, with just 1500 images of data the RAM(i.e. 12GB) was reaching it's limit but major problem was GPU(i.e. 12 GB) memory was getting totally exhausted with addition of few convolutional layers. Therefore, I decided to go ahead with the Green channel only along with 1000 training images 500 images of symptoms and 500 non-symptom images along with 105 images in the validation set.

Given if memory allocation was more, then image augmentation could've been possible with different angular rotations.

3. CONCLUSION

Through the article, we learned about what medical imaging is and how important it has become in the current healthcare scenario. We look at the different kinds of medical imaging techniques, how they are performed and what kind of disease diagnosis they help with. We delved deep into several different kinds of diseases and applications of deep learning in the same, reviewing literature across various spheres of the sector. We looked at some regulatory concerns and important research objectives following which, we implemented a CNN model for binary classification of fundus images for the detection of diabetic retinopathy.

This provides a complete walkthrough on the project on detecting blindness in the retina images using CNNs. We use image preprocessing to reduce discrepancies across images taken in different clinics, apply transfer learning to leverage knowledge from larger data sets and implement different techniques to improve performance. You might be wondering about ways to further improve the solution. There are multiple options. First, employing larger network architecture and increasing the number of training epochs on the pre-training stage has a high potential for a better performance. At the same time, this would require more computing power, which might not be optimal considering the possible use of the automated retina image classification in practice. Second, image preprocessing can be further improved. During the refinement process, the largest performance gains were attributed to different preprocessing steps. This is a more efficient way to further improve the performance.

Finally, the best solutions of other competitors rely on ensembles of CNNs using different image sizes and/or architectures. Incorporating multiple heterogeneous models and blending their predictions could also improve the proposed solution. Ensembling predictions of models similar to the one discussed in this post is what helped me to place in the top 9% of the leaderboard.

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