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AI DIET CONSULTANT MANAGEMENT SYSTEM

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Abstract *- Early detection of cancer is necessary for many people's lives to be saved. For these types of cancer diagnoses, visual inspection and manual procedures are typically used. This method of manually interpreting medical images takes a long time and is vulnerable to errors. As a result, in this project, a novel deep learning architecture is used to identify various types of cancer and detect their existence without the need for multiple doctor consultations. This helps us to foresee the existence of the disease sooner and take decisive action to prevent more effects in a cost-effective and timely manner, reducing the rate of human error. This project investigates five different cancers, including lung cancer, brain tumours, cervical cancer, skin cancer, and breast cancer. A web application will be created as a hospital application that will use an x-ray image as input to determine which type of cancer is present. Food suggestions will be provided to the user for that particular type of cancer.*

I. INTRODUCTION

According to a major study, the most common 5 types of cancers are taken into account. Patients at risk of cancer may have a few symptoms, so they are recommended to have a CT scan. The results of the scans will be used to identify the patient, and diet recommendations will be made based on the stage of cancer.This method aids in faster diagnosis and also assists patients with food recommendations based on a random forest algorithm.

II. EXISTING SYSTEM

In radiomic studies with a large number of features, feature dimensionality reduction is important. Conventional radiomic methods, on the other hand, may suffer from noise, and feature dimensionality reduction techniques are not designed to learn discriminative low-dimensional representations using latent supervision information from the patient data under analysis, such as differences in patients. We create a robust collaborative clustering method to simultaneously cluster patients and radiomic features into distinct groups under adaptive sparse regularisation to achieve robustness to noise and feature dimensionality reduction with improved discriminative capacity. For simultaneous function dimensionality reduction and denoising, our approach uses matrix tri-factorization with adaptive sparsity regularisation. In particular, latent grouping information of patients with different radiomic features is learned and used as supervision information to direct feature dimensionality reduction, and noise in radiomic features is adaptively isolated in a Bayesian system using Laplacian distributions of transform-domain coefficients.

DISADVANTAGES OF EXISTING SYSTEM:

- The existing system has focused on only one type of cancer diagnosis.
- Most of the training data is redundant
- Accuracy is less
- Only the methods of diagnosis are proposed.

III. LITERATURE REVIEW

To achieve robustness to noise and feature dimensionality reduction with improved discriminative power, we develop a robust collaborative clustering method [1] to simultaneously cluster patients and radiomic features into distinct groups respectively under adaptive sparse regularization.Normal and malignant skin tissues are separately mimicked by using appropriate mixtures of deionized water, oil, gelatin powder, formaldehyde,[2] TX-150 (a gelling agent, widely referred to as 'super stuff'), and detergent.This technique provides an automatic and accurate CADe scheme for breast screening by having high sensitivity and low false positives, and may assist other advanced applications,[3] such as size measurement, lesion characterization, and BI-RADS categorization.

IV. PROPOSED SYSTEM

On a global scale, cancer is the leading cause of death. Cancer is a difficult disease to combat for both researchers and physicians. In 2019, the American Cancer Society predicts 96,480 deaths from skin cancer, 142,670 deaths from lung cancer, 42,260 deaths from breast cancer, 31,620 deaths from prostate cancer, and 17,760 deaths from brain cancer (American Cancer Society, new cancer release report 2019). Early detection of cancer is the top priority for saving the lives of many. Typically, visual examination and manual techniques are used for these types of cancer diagnosis. This manual interpretation of medical images demands high time consumption and is highly prone to mistakes. Thus in this project we apply deep learning algorithms to classify between the different types of cancer and detect its presence without the need of a number of consultations from different doctors. This leads to earlier prediction of the presence of the disease and allows us to take prior actions immediately to avoid further consequences in an effective and cheap manner avoiding human error rate. In this project five different types of cancer such as lung cancer, brain tumour, cervical cancer, breast cancer and eye glaucoma are determined. A web application will be developed as a hospital application where an input CT scan image will be given to predict which type of cancer. A diet suggestion will be provided to the user for that specific type of cancer.

V. ARCHITECTURE DIAGRAM

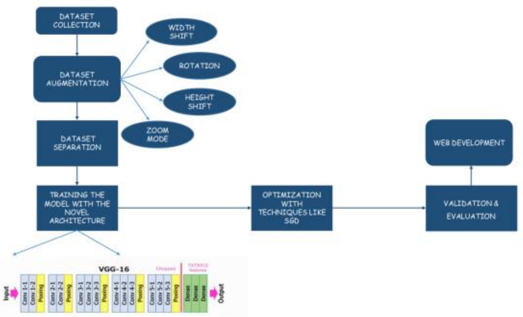


fig 5.1 Architecture flow of our website

VI. MODULE

A) Data Collection

A data set is a set of information. Deep Learning has emerged as the preferred tool for tackling a wide range of difficult real-world problems. It is, without a doubt, the most effective approach for computer vision tasks. Deep learning's strength in computer vision is demonstrated in the picture above. A deep network can segment and classify the "key points" of any individual in an image with enough training. These deep learning machines, which have been performing admirably, need a lot of power, which is data. Our model performs better when there is more labelled data available. Google has also experimented with the concept of more data contributing to better results on a wide scale, with a dataset of 300 million images! When using a Deep Learning model in a real-world application, it must be fed data on a regular basis in order to improve its efficiency. Data is, without a doubt, the most important resource in the deep learning period. The data collection process is divided into three stages.

Scraping From the Web

- Because of the amount of human effort involved, manually locating and uploading pictures takes a long time. Detecting common items is most likely part of the mission. As a result, the term "internet scraping" is coined. It also becomes the object's class name. Every pixel in the image must be used. It's best to use some of the many excellent image annotation resources that are already available. Can generate pixel labels for segmentation given a rough collection of polygon points around an object. Deep extreme cut is identical to deep extreme cut, except that only the four extreme points around the object are used. This will result in some cool segmentation and bounding box labels. Another alternative is to use an image annotation GUI that already exists.

Third-party:

Since data has become such a valuable asset in the deep learning era, many start-ups have begun to offer their own image annotation services, where they can collect and mark data. Given a summary of the data and annotations that are needed. Mighty, a company that specialises in self-driving car image annotation and has grown to be a major player in the field, was also present at CVPR 2018. Payment AI is less specialised than Mighty AI, and it can annotate images from any domain.

B) Data Augmentation

The performance of deep learning neural networks often improves with the amount of data available.

Data augmentation is a method of artificially creating new training data from existing data. This is accomplished by using domain-specific techniques to transform examples from the training data into new and unique training examples.

The most well-known method of data augmentation is image data augmentation, which entails transforming images in the training dataset into transformed versions that belong to the same class as the original image.

Shifts, turns, zooms, and other operations from the field of image processing are included in transforms.

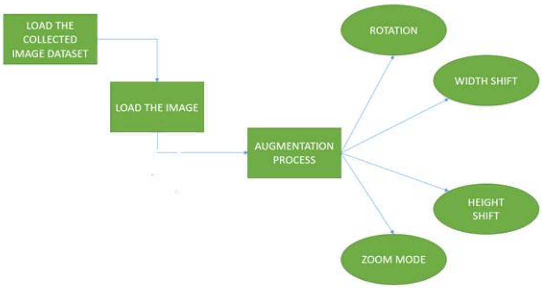
The aim is to add new, plausible examples to the training dataset. This refers to variants of the training set images that the model is likely to see. A horizontal flip of a cat photo, for example, would make sense because the photo could have been taken from either the left or right. A vertical flip of a cat photo makes little sense and would almost certainly be inappropriate, considering that the model is unlikely to see an upside-down cat photo.

As a result, it's obvious that the particular data augmentation strategies used for a training dataset must be carefully selected, taking into account the training dataset as well as awareness of the problem domain. Furthermore, it can be beneficial to test data augmentation methods separately and in combination to see if they result in a measurable improvement in model performance, possibly with a small prototype dataset, model, and training run.

Deep learning algorithms, such as the convolutional neural network, or CNN, can learn features that are independent of their location in an image. Nonetheless, augmentation can help with this transform-invariant approach to learning by assisting the model in learning features that are also transform-invariant, such as left-to-right to top-to-bottom ordering, light levels in photographs, and more.

Typically, image data augmentation is applied only to the training dataset and not to the validation or test dataset. This is distinct from data preparation tasks like image resizing and pixel scaling, which must be carried out consistently across all datasets that interact with the model.

Image before augmentation



C) Penta cancer prediction using the architecture:

In this project, the VGG-16 algorithm is used for training the model. The VGG16 algorithm will be used to train the model. VGG16 is a convolutional neural network model proposed in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" by K. Simonyan and A. Zisserman of the University of Oxford. In ImageNet, a dataset of over 14 million images classified into 1000 classes, the model achieves 92.7 percent top-5 test accuracy. It was one of the famous models submitted to ILSVRC-2014. It was one of the well-known models entered in the ILSVRC-2014. It outperforms AlexNet by replacing large kernel-sized filters (11 and 5, respectively, in the first and second convolutional layers) with multiple 33 kernel-sized filters one after the other. VGG16 had been training for weeks on the NVIDIA Titan Black GPU.

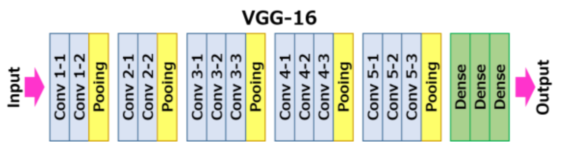


Figure 4.4: VGG-16 Input Output

ImageNet is a collection of over 15 million labelled high-resolution images organised into approximately 22,000 categories. The images were gathered from the internet and tagged by humans using Amazon's Mechanical Turk crowd-sourcing tool. An annual competition called the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) has been held as part of the Pascal Visual Object Challenge since 2010. ILSVRC employs a subset of ImageNet, with approximately 1000 images in each of the 1000 categories. There are approximately 1.2 million training images, 50,000 validation images, and 150,000 testing images in total. ImageNet is made up of images with varying resolutions. As a result, the images were downsampled to a fixed resolution of 256x256. Given a rectangular image, it is resized and the central 256x256 patch is cropped out of the resulting image.

The cov1 layer receives a 224 x 224 RGB image as input. The image is passed through a stack of convolutional (conv.) layers, with the filters set to capture the notions of left/right, up/down, and centre with a very small receptive field: 33 (the smallest size to capture the notions of left/right, up/down, and centre). It also employs 11 convolution filters in one of the configurations, which can be thought of as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed at 1 pixel; the spatial padding of conv. layer input is set so that the spatial resolution is preserved after convolution, i.e. 1-pixel padding for 33 conv. layers. Five max-pooling layers follow some of the conv. layers and perform spatial pooling (not all the conv. layers are followed by max-pooling). Max-pooling is done with stride 2 over a 22 pixel window.

Following a stack of convolutional layers (with varying depths in different architectures), three Fully-Connected (FC) layers are added: the first two have 4096 channels each, while the third performs 1000-way ILSVRC classification and thus has 1000 channels (one for each class). The soft-max layer is the final layer. In all networks, the configuration of the fully connected layers is the same.

The rectification (ReLU) non-linearity is present in all hidden layers. It is also worth noting that none of the networks (except one) use Local Response Normalization (LRN), which does not improve performance on the ILSVRC dataset but increases memory consumption and computation time.

D) MongoDb integration

In this project, MongoDB is used for database integration.

MongoDB is a document-oriented database that is cross-platform and offers high performance, high availability, and easy scalability. MongoDB is based on the collection and document concepts.

Database

A database is a physical storage location for collections. On the file system, each database has its own set of files. Multiple databases are typically housed on a single MongoDB server.

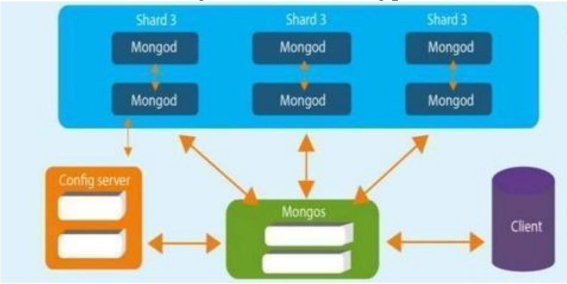
Collection

Collection is a group of MongoDB documents. It is the equivalent of an RDBMS table. A collection exists within a single database. Collections do not enforce a schema. Documents within a collection can have different fields.

Typically, all documents in a collection are of similar or related purpose.

Document

A document is a set of key-value pairs. Documents have a dynamic schema. Dynamic schema means that documents in the same collection do not need to have the same set of fields or structure, and common fields in a collection's documents may hold different types of data.

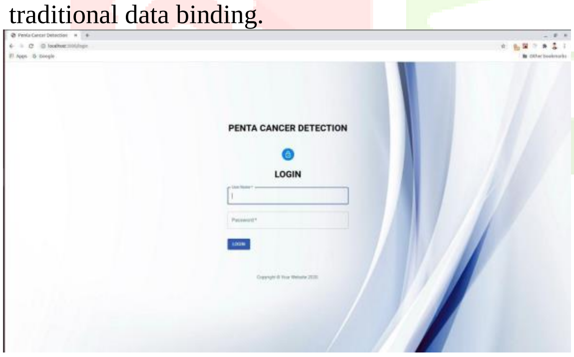


Architecture diagram of MONGODB

E) WEB APPLICATION DEVELOPMENT

ReactJS is a JavaScript library used for building reusable UI components. According to React official documentation, following is the definition −

React is a library that allows you to create reusable user interfaces. It promotes the development of reusable UI components that display data that changes over time. React is commonly used as the V in MVC. React abstracts the DOM from you, resulting in a simpler programming model and improved performance. React can also be used to render on the server with Node, and it can power native apps with React Native. React implements one-way reactive data flow, which reduces boilerplate and makes reasoning easier than traditional data binding.

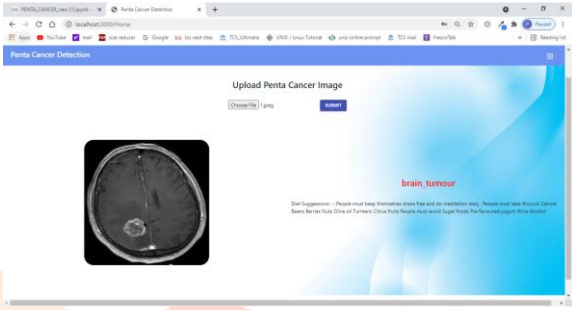


Website Login Page

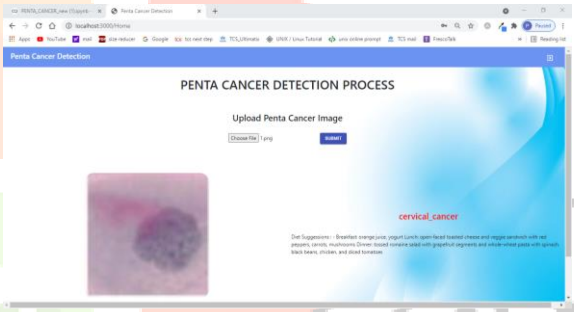
F) DIET SUGGESTION

After determining the type of cancer, it will be determined whether it is in stage 1 or stage 2. The patient will be given food suggestions based on that. Eating and fasting have long been thought to be diametrically opposed. However, the actual fact is that it is not true. Dieting allows both to work well together. Dieting has been plagued by a slew of myths. Dieting without proper knowledge or guidance can also lead to a variety of inherent diseases. As a result, there are numerous paediatricians and other doctors who seek to guide people toward a healthy lifestyle. There are, however, a number of diet consultant apps on the market to assist doctors and paediatricians. However, many of them are ineffective and inefficient because they are not appropriate for different people, because different people have different staple foods and a specific diet may not work for them. So, in order to bridge that gap, we propose a new AI-based Diet Consultant System in which different people have their own customised diet plans created for them. This model also employs the Random Forest algorithm for the system, which is a lightweight system that does not require a large amount of data and is thus efficient. In addition, unlike the existing system, the proposed system does not require a large training dataset. Furthermore, the system boasts an accuracy of 81 percent, which is significantly higher than any other implemented system. As a result, the proposed system addresses all of the shortcomings of existing systems while being far more reliable and user friendly.

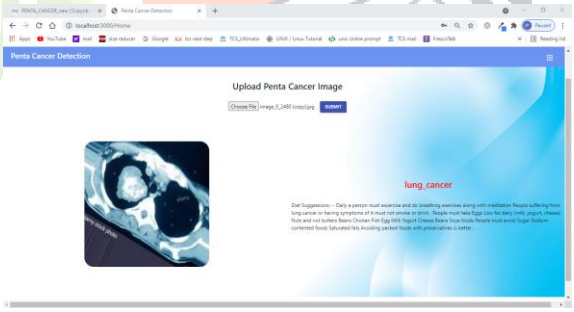
VII. OUTPUT



Brain tumour detection



Cervical Cancer detection



Lung Cancer detection

VIII. CONCLUSION

The project has been successfully implemented to detect the presence of five types of cancers and determine whether the person has cervical cancer, lung cancer or brain tumour and provide prior measures to avoid the disease. This also aids in providing efficient treatment at the lowest possible cost, ultimately shortening the time required to detect cancer. In its current state, it is done manually, which takes more time and involves a higher rate of human error. As a result, this project reduces the time required for manual classification and eliminates the rate of human error. In the near future, we will examine the application of cancer determinant technology in the healthcare field, and how it can improve the detection of various types of cancer with greater accuracy. In the medical field, they have more opportunities to develop or convert this project in a variety of ways. As a result, this project has a promising future in which manual forecasting can be converted to computerised production at a low cost.

IX. REFERENCES :

[1] Amir Mirbeik-Sabzevari, Student Member, IEEE, Negar Tavassolian, Senior Member, IEEE “Ultra-Wideband, Stable Normal and Cancer Skin Tissue Phantoms for Millimeter-Wave Skin Cancer Imaging”, IEEE Transactions on Biomedical Engineering.

[2] Annette McWilliams*, Parmida Beigi*, Akhila Srinidhi, Stephen Lam, and Calum E. MacAulay “Sex and Smoking Status Effects on the Early Detection of Early Lung Cancer in High-Risk Smokers using an Electronic Nose” IEEE Transactions on Biomedical Engineering.

[3] Arnaud A. A. Setio, Francesco Ciompi, Geert Litjens, Paul Gerke, Colin Jacobs, Sarah J. van Riel, Mathilde Marie Winkler Wille, Matiullah Naqibullah, Clara I. S´anchez, Bram van Ginneken ``Pulmonary nodule detection in CT images: false positive reduction using multi-view convolutional networks” IEEE Transactions on Medical Imaging.

[4] Hua Zhong and Mingzhou Song “A fast exact functional test for directional association and cancer biology applications” IEEE/ACM Transactions on Computational Biology and Bioinformatics.

[5] Jose M. Anton-Rodriguez, Peter Julyan, Ibrahim Djoukhadar, David Russell, D. Gareth Evans, Alan Jackson, and Julian C. Matthews “Comparison of a Standard Resolution PET-CT Scanner With an HRRT Brain Scanner for Imaging Small Tumors Within the Head” IEEE transactions on radiation and plasma medical sciences, vol. 3, no. 4, july 2019.