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Digitalization of Medical Records supported with the Analysis of Medical Scans using Deep Learning

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ABSTRACT
Nowadays, many patients find difficulty in maintaining their medical reports. So, if we have a website which records and manages the reports of patients it will be useful for them to access as well as it will be kept safe. For this, an attempt was made to design a website and store the database containing the reports of the patients. Furthermore, the website will contain a Deep Learning-based analyzer that analyzes certain medical scans uploaded. CNN algorithm was used to analyze medical images, since deep learning algorithms have taken over the processing of medical images. The medical scan reports of the patients provide the appropriate information about it with a high accuracy.
Keywords—Convolutional Neural Network, medical scans, medical records, deep learning

1. Introduction
The main objective is to create and maintain a website with the patients health records which can be accessed by the patients as well as the hospitals using the Unique Identification Number of the patients. We have made use of Deep Learning to provide appropriate information about the scan reports of the patients. In part due to the less organized and labeled nature of medical image analysis, deep learning is the oldest active study of the field and it is likely that this will be a place where patients come into contact with the functional, strategies of wisdom. It provides a human-AI testbed communication, about how the receiving patients will be in relation to the choice of health change being performed, or the assistance of a non- person actor.

2. Literature Survey
2.1 *Convolutional Neural Network :*
CNNs are highly researched machine learning algorithms that are used for medical image analysis. This is due to the fact that CNNs maintain local relationships while screening input images. As mentioned, local relationships are very important in radiology, for example, on the edges of bone meets the muscles, or where normal lung tissue contact with cancerous tissues with Flexible Layers, Adjusted Linear Units (RELU) and Pooling Layers, CNN converts an input image of green pixels. Solution is defined as the performance of two functions images are analyzed in two different ways: in one case by containing input values (e.g. pixels); in the other case by using a filter (or kernel), which is represented by a number. Calculation of product dots between two tasks give effect. A step length is subsequently used to determine where the filter is placed next in the image. The count is repeated until the whole picture is covered, to generate a feature map (or activation). It shows where the filter is currently active and has picked up features such as straight lines, dots, or curved edges. If the image of faces featured on CNN, features low-key initially like lines and edges are obtained by filters. This is constructive in progressively higher aspects in the following layers, e.g: nose, eye or ear, as feature maps become the input of the next layer in the construction of CNN. Convolution uses three internal ideas to do it computationally efficient: a few measurements, partial sharing (or weight

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sharing) and equation (or constant) representation. Unlike other neural net functions where all the input neuron is connected to all outlet neuron in the next layer, CNN neurons have less connection, which means that only certain inputs are connected to the following layer. By having a small, well-located area (e.g., the area covered by the filter at each step), each feature can be studied gradually, the calculation can be greatly reduced, increasing the algorithm efficiency. In applying each filter with its own adjustment weights in various domains of the whole image, CNN reducing memory storage requirements called Parameter sharing. Parameter sharing results in the quality of equitable representation that will emerge. . This means that the input translation results in the mapping of the same feature. The convolution function is defined by * mark. Output (or feature map) is described below where input I(t) is indicated by a filter or button K (a).

$$s(t) = (I*K)(t).$$

RELU layer functionality to activate incorrect settings input values to zero. This simplifies and accelerate training and training statistics, and helps to avoid a missing gradient the problem. From a statistical perspective, it is calculated as:

$$f(x) = \text{plural}(0, x).$$

when x is inserted into a neuron. In addition to sigmoid, tanh, leaky RELUs, Randomized RELUs, and RELUs for parametric, there are also RELUs which are not linear. To reduce the number of parameter calculations and image sizes (width and height only, not depth), the Pooling layer is inserted between Convolution and RELU layers. Max-pooling is widely used; other integration layers include medium and standard L2 divisions to combine. Max-pooling simply takes a very large installation value inside the filter and discard some values, effectively measures the strongest performance in the area. There is a sense of importance placed on one way of the area over another.
An integrated layer, the last on CNN, is made up of neurons from every previous layer connected to neurons in the fully integrated layer. Like convolution, RELU and integration layers, may be present or fully connected layers by level of desired feature release. This layer captures output from the previous layer (Convolutional, RELU or Pooling) as input, and calculates points that may be included in a paragraph different class available. In fact, this layer looks great in the integration of the most open elements that will show that the image is in a certain category. For example, on slides in histology glass, cancer cells have a higher rate of DNA and cytoplasm compared to normal cells. CNN will be able to predict cancer cells' presence if DNA traits from the past layer are established. Common methods of neural network training with backpropagation and a decrease in stochastic gradient help CNN learn organizations that are important for training pictures.

3. Existing System

The classification of images and other computer- based tasks is improved by convolutional neural networks (CNNs).

1. Fire detection systems that utilize CNN have greatly improved detection accuracy, ultimately reducing fire hazards and environmental and social degradation.

2. Using CNN-SkelPose, clinical bone measurements can be made. A CNN-SkelPose extracts local and international information from depth images using a Convolutional Neural Network. CNN-SkelPose exceeds the basic Skeltrack model for relieving skeleton models that are reliable in patient monitoring situations.

3. As the appearance, complexity, and background of real-world video surveillance applications vary, detecting faces is challenging. Recent research has suggested several CNN designs to enhance accuracy, but their computer complexity can pose difficulties, especially in real-time applications where high-resolution cameras need to be used to detect faces and heads live. The computational

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costs associated with CNNs can reflect the limitations of many real-time applications, even though they can achieve a much higher level of accuracy compared to traditional detectors.

4. Classifying hyperspectral images (HSIs) in remote sensing is a very important function with a wide range of applications. Convolutional Neural Networks (CNN) have shown to perform well among the many approaches proposed over the years. Agricultural, forestry and food processing applications can benefit from this technology.

5. Various agricultural problems can be solved by using deep learning, such as diagnosing, classifying fruits and crops, and counting fruits. This method provides precise results that are superior to other ways of processing images, including deep reading, because deep reading is highly accurate.

6. Detection of an online food image is a key issue for food supply chain applications, how to get the right, accurate and quickly detect the image of the food materials is a challenge There was a previous proposal of using fast- paced convolutional neural networks (CNNs) to detect food materials online, which dealt with issues related to food complexity, concentration, and lighting. In addition to increasing efficiency in the food procurement industry and ensuring food quality, the proposed model and algorithm have been effective and accurate.

7. Space-based space surveillance (SBSS) of targeted space objects often suffers from low spatial adjustment due to the very long distance between the target and the imaging sensor. For the most specific images, data processing functions such as image super-resolution can be effectively used. A convolutional neural network (CNN)- based model for single image resolution was developed as a result.

8. The mapping of open water and sea ice is key for a variety of projects. Seawater and open water classification must be accurate and dynamic in order to support ice resources. With the availability of a large database of highly efficient imaging and computer programs, convolutional neural networks (CNNs) are becoming increasingly popular in many research communities. Therefore, CNN has been used in this regard and the complete accuracy of the 92.36% segment was achieved based on the data of the tests performed.

as illustrated in Fig. 3. The composition of the elements contained in the material is shown in Fig. 2 by the EDAX analysis. Table 4 shows the elemental compositions of cement and GGBS. Higher component values are determined by high-intensity peaks.

4. Proposed System

4.1 CNN for Medical Scan Analysis:

Convolution Neural Network can be used for analysing the scan reports of the patients. There are different types of medical scans such as, MRI Scan, CT Scan, X-Ray, Ultrasound, Fluoroscopy etc. Images of internal organs or body parts are produced by these types of scans. Patients are diagnosed with disease using these images by health care professionals. But this can be done with the help of Convolutional Neural Network to analyse the scan reports of the patients. The system can be trained with numerous scan report images of the normal and diseased health conditions of the patients. This can further be validated and then tested with different datasets.
This system can be interfaced with the website so that the users can easily upload their scan reports in the scan analysing tool and get their results within minutes and they need not seek for a doctor to analyse their scan reports. This makes the work simple and efficient .

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5. Block Diagram

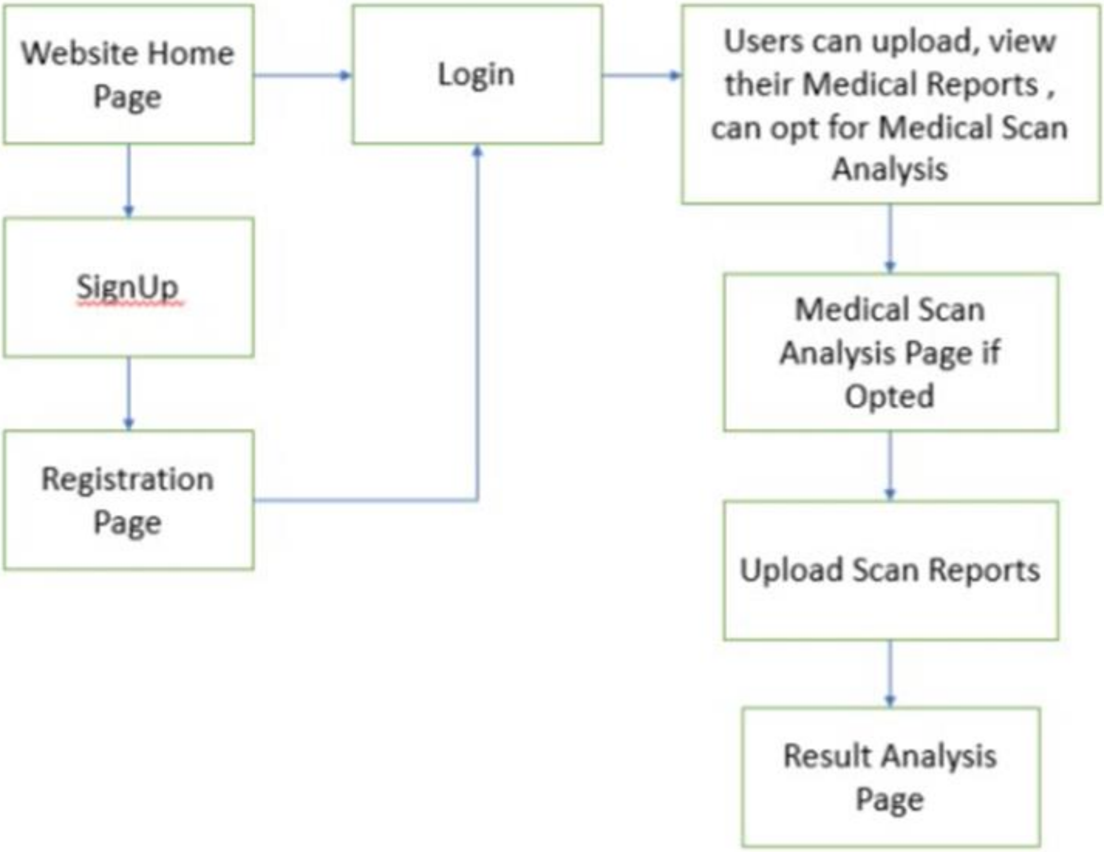

Fig1.1 Flow of Web Page

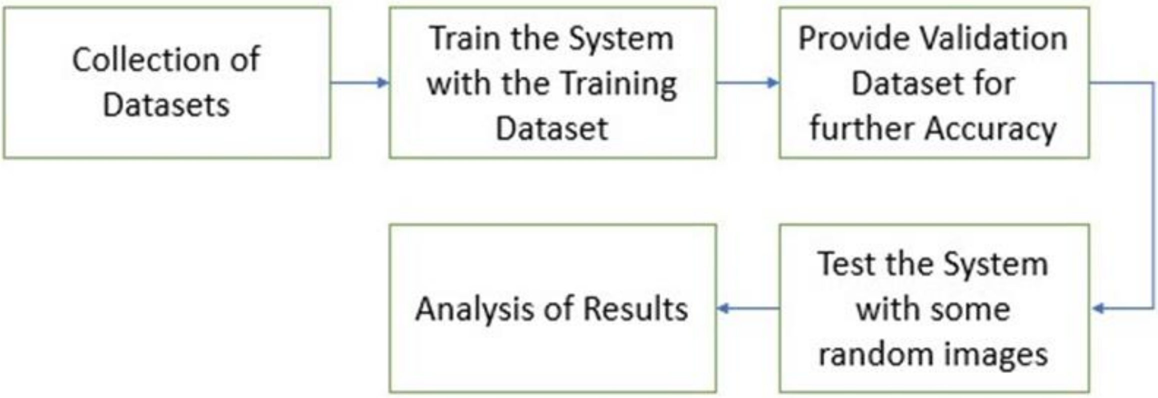

Fig1.2 Convolutional Neural Network System

6. Working

Figure 1.1 illustrates the block diagram of the Web Page. To be able to log in, the user needs to be already registered, otherwise registration must be completed before accessing the page. Once login was done, he/she shall upload the medical reports, which will be maintained in our database. The user can upload and view his/her medical reports whenever he wishes to. The website is provided with the feature of Medical Scan Analysis. So, if an user opts for it, he/she can upload the scan reports and press the analyse button to know about the health condition. The Scan analysing system was trained with a set of images and the system was validated with a set of images also the system

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was tested against few random images. The system predicts the patient's health conditions based on the image when the user uploads it for analysis.

7. Software Tools Required

A. Visual Studio Code (For Web Development):

Source code editing is supported for HTML, CSS, JavaScript, Go, Node.js, Python and C++ using Visual Studio Code. The workspace allows users to open one or more indexes, which can be saved for later use instead of a project plan. Multiple programming languages are supported, each with their own set of features. The project tree can be cleaned up by deleting unwanted files and folders. Many features of the Visual Studio Code are not displayed in the menus or user interface but they can be accessed through the command palette. A number of FTP extensions are included in Visual Studio code, making it an alternative to web development that is free. Code synchronization between the editor and server does not require additional software. It is possible for users to specify the code page where the active document is stored, the new character, and the language of a program that uses an active document in Visual Studio. Any platform, anywhere, and any programming language can be used with it.

B. Anaconda:

Users can control conda packages, locations, and channels without using command line commands by using Anaconda Navigator, a desktop user interface (GUI) embedded in Anaconda distribution A package can be found, installed, applied, and updated using Navigator in the Anaconda Cloud or Anaconda repository. There are a number of Python packages, textbooks, and locations hosted in the cloud that can be useful.

C. Jupyter Lab:

Project Jupyter Lab shows off a new user interface that enables you to build a Jupyter Notebook on your computer (notebook, endpoint, text editor, file browser, rich results, etc.).

8. Result

The system was trained and tested to analyse the CT Scan of Brain and provide the result whether the brain condition of the patient is normal or affected by tumour. Further we are working on other types of medical scans also, we hope we shall complete the training and testing part of our system to analyse the medical scans of other internal organs as soon as possible.

9. Future Scope

Regional languages can be made available in the website so that the people in rural areas, not familiar with English can also use it in an easier and efficient way. More security features can also be added to the website. Features like maintaining the Blood Groups of the people in different regions can be made available in the website and the access to view the Blood Groups of the people with few of their information like contact number and address of the donors can be given to the people who visits the website.

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