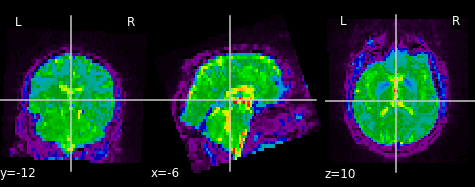
**ABSTRACT**

Recognition of Parkinson's malady (PD) in early stages is significant which can empower early commencement of restorative mediations and the executive’s procedures. Be that as it may, techniques for early recognition still stay a neglected clinical need in PD. Early administration as when sign of clinical manifestations happen, more than 60 % of the dopaminergic neurons have just been lost. It is presently settled that there exists a premotor organize, before the beginning of these great engine side effects, described by a star grouping of clinical highlights, for the most part non-engine in nature, for example, Rapid Eye Movement (REM) rest Behavior Disorder (RBD) and olfactory misfortune. In this project, we used the different images of two unique groups that can order early PD from cerebrum pictures utilizing deep neural networks that are getting prominent in biomedicine. We completed both subject-wise and year wise prediction for validating the model that we constructed. We see that these systems perform with high precision and high accuracy which is 100% in detecting early Parkinson Disease. The calculated model exhibited factually noteworthy fit to the data showing its convenience as a prescient model. It is induced that these forecast models can possibly help clinicians in the symptomatic procedure by joining the things of a poll through picture characterization utilizing profound learning. Moreover, as we proceed through getting the data, we got the data from the supervisor who managed the data from other organizations. Thus we proceed through working along the process of detecting Parkinson disease using neuromagnetic images and were able to detect Parkinson disease successfully. Neuromagnetic recordings allow noninvasive localization of electrical sources in the human brain. To improve such localization methods, we have developed systems for: 1) digitizing the head surface at high resolution; 2) displaying measured neuromagnetic field distributions on the resulting model; 3) locating estimated neuromagnetic sources on magnetic resonance images (MRI); and 4) performing 3-dimensional volumetric reconstructions of brain structures from a series of MRI scans. These systems facilitate the localization of sources of neuromagnetic activity and permit visualization of the anatomical context of such sources.

**INTRODUCTION**

Neuromagnetic measurements together with appropriate mathematical models permit the localization of electrical sources in the human brain. An array of SQUID-coupled gradiometer sensors can be used to noninvasively measure the intensity of magnetic fields at the head surface evoked by sensory stimulation. Field maps produced in this manner can be fit with models derived from simple source configurations. For large evoked response components, Monte Carlo error analyses suggest that source location uncertainty due to measurement noise may be as low as 1 mm. However, in order to achieve and exploit this degree of accuracy in source localization it is necessary to improve procedures for documenting the geometry of the head and the relative location of sensors, and for locating anatomical sources which account for observed fields. To satisfy these perceived needs, we have developed systems for modeling and displaying the three dimensional structure of the head and brain.



A shaded rendering of the head can be generated and manipulated using software or hardware subsystems, and a pseudo color map of observed evoked response fields can be painted onto the head surface model. Animated sequences of such images can be assembled to illustrate the response time course. A second system allows neuromagnetic sources to be located on magnetic resonance images. The system facilitates the reconciliation of neuromagnetic and MRI coordinate systems, selects the appropriate images from series of sagittal, axial and coronal slices, and prepares an orthographic rendering of the calculated source. A third system allows the production and manipulation of a 3-D volumetric model of brain structure from MRI data. In the diagnosis of radiological images, detection and classification processes are important. Brain diseases such as Parkinson Disease have wide variations. They include many clinical important factors. For assisting radiologists’ diagnosis, computer-aided diagnosis (CAD) systems include two types of CAD algorithms such as a computer-aided detection (CADe) that detect abnormal lesion, and a computer aided diagnosis (CADx) that differentiate abnormal lesion into benign or malignant. In previous CAD algorithms, we used image features that could detect and classify lung abnormalities such as lung nodules or diffuse lung disease patterns. These image features are useful for computer-aided classification on lung diseases. However, to define such image features is a difficult task due to complicated image patterns of different groups of Parkinson diseases. Deep learning technique has dramatically improved the state-of-the art in pattern recognition in the fields of computer vison. Moreover, convolutional neural network (CNN) has brought about breakthrough in pattern recognition of images including medical images. In usual CAD algorithms, designing an image-feature extractor is important. However, this task is difficult. On the other hand, a CAD algorithm by use of CNN does not necessarily require the image-feature extractor. In this study, we have developed an image-based algorithm for differential diagnosis of brain abnormalities and found out different groups of Parkinson Disease by use of CNN. CNN shows high performance for classification of natural images. Therefore, many researchers have studied about differential diagnosis neural images.

**LITERATURE REVIEW**

Non-motor features affect the quality of life equally or more than the motor features in PD. Among these non-motor features, hyposmia (olfactory dysfunction) and RBD are the most common ones. Studies have shown that profound olfactory deficits in the form of impairments in odor detection, differentiation, and identification are observed at the earliest clinical stage of PD indicating that olfactory dysfunction is a prodromal or 3

preclinical sign [6]. Ponsen et al. performed a study on a cohort of 361 asymptomatic relatives of PD patients, and observed that idiopathic olfactory dysfunction is associated with an increased risk of developing PD of at least 10% [6].

RBD is another non-motor symptom which often antedates a neurodegenerative disorders such as PD [7]. It is a disturbance associated with sleep and is characterized by vivid, aggressive or action-packed dreams, dream enacting behaviours such as shouting, punching, and loss of normal REM-sleep muscle atonia [7]. Studies show that subjects diagnosed with RBD are at high risk of developing neurodegenerative diseases, most importantly PD [7, 8]. Postuma et al. performed a clinical follow-up study for 12 years on 93 subjects with RBD, and observed that over this period, 26 (28%) developed neurodegenerative disorders of which 14 (15%) were PD. From this study, they also estimated the 5-year risk, 10-year risk and 12-year risk of neurodegenerative disease in idiopathic RBD as 17.7%, 40.6% and 52.4% respectively [8].

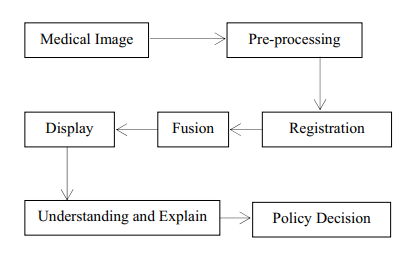
CSF markers of amyloid beta peptide 1-42 (Aβ1-42), total tau (T-tau), tau phosphorylated at threonine 181 (P-tau181) and α-synuclein (α-Syn) are now widely researched biomarkers for the diagnosis of neurodegenerative disorders [9]. CSF have the advantage that they are more accessible, less costly than imaging, reflect metabolic and pathological states of the central nervous system (CNS) more directly than any other body fluids [10]. Recent studies have shown that CSF markers hold promise in detecting PD, but they are still in early stages of development [2]. For instance, Kang et al. performed a study with 63 early PD and 39 healthy normal subjects from the Parkinson's Progression Markers Initiative (PPMI) database, and observed a significant decrease in levels of Aβ1-42, T-tau, P-tau181, α-Syn and T-tau/Aβ1-42 in PD as compared to healthy normal indicating their prognostic and diagnostic potential in early-stage PD [11]. However, they also observed that the diagnostic utility of these CSF markers is low as the area under the ROC curve (AUC) were less than 80% and that a combination with other significant biomarkers is likely to improve diagnostic accuracy.

There are studies which use these features to classify subjects as early PD and healthy normal [11, 14-22]. [14] performed smell identification tests using culturally adapted translations of the University of Pennsylvania Smell Identification Test (UPSIT) and Sniffin‟ Sticks (SS) test in 106 PD and 118 normal subjects. They observed the following performance measures using logistic regression for classification. Using SS test: 85.3% accuracy, 81.1% sensitivity and 89% specificity; and using UPSIT: 82.8% accuracy, 82.1% sensitivity and 83.5% specificity. [15] improved the same study by including more subjects, from 193 PD and 157 normal subjects, and using logistic regression, they observed an enhanced classification accuracy with both SS test and UPSIT with highest performance obtained with the SS test as 88.4% accuracy, 90.4% sensitivity and 85.5 % specificity. [16] used non-motor features such as cognitive impairment, psychiatric complications, autonomic dysfunction or sleep disturbance, from 410 PD patients, to classify subjects based on disease severity as mild, moderate and severe, and they obtained classification accuracies in the range of 72%−92%. [11] used Cerebrospinal Fluid (CSF) measurements from 63 early PD and 39 healthy normal and observed that these measures were statistically significant but showed a low diagnostic 5

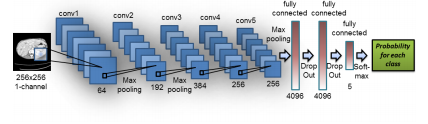
utility as the area under the ROC (AUC) was less than 0.8 for PD diagnosis. [17] used 123I-Ioflupane (DaTSCANTM, GE Healthcare; also known as [123I] FP-CIT) SPECT scan data from 79 patients with parkinsonism (PS) and 37 non-PS subjects (which is not the healthy normal group and instead it represents subjects with non-PS conditions like essential tremor that shows normal SPECT scans), and obtained a classification accuracy of 94.8% with 93.7% sensitivity and 97.3 % specificity using Naïve Bayes classifier. [18] also used SPECT scan data from 95 PD and 94 normal subjects and obtained a maximum accuracy of 94.7%, sensitivity 93.7 % and specificity 95.7% using an approach based on partial least squares and support vector machine (SVM). [19] used SPECT scan data from 108 PS and 100 normal subjects and using CNN obtained a sensitivity of 100%, specificity as 100 %. [20] used Striatal Binding Ratio (SBR) values from SPECT imaging corresponding to 369 early PD and 179 normal subjects from the PPMI database and obtained a maximum classification accuracy of 100% using Deep Learning Classifier. [21] carried out speech analysis to extract features for classification between speech symptom severity levels using SVM. They obtained accuracy of around 100% with average AUC around 91%. [22] carry out detection of Parkinson‟s disease (PD) from speech signal measurements using machine learning techniques such as logistic regression, SVM, ensemble methods etc. The data used for the study consisted of 31 normal and 23 PD subjects. They obtain encouraging results. However, these studies had the limitation that none of these studies used a combination of features for performing the classification or had small sample size.

**METHODOLOGY**

2.1. Convolutional networks In this work, we apply ConvNets to build an anatomy-specific classifier for CT images. ConvNets are named for their convolutional filters which are used to compute image features. for classification. In this work, we use 5 cascaded layers of convolutional filters. All convolutional filter kernel elements are trained from the data in a supervised fashion.



This has major advantages over more traditional CAD approaches that use hand-crafted features, designed from human experience. This means that ConvNets have a better chance of capturing the “essence” of the imaging data set used for training than when using hand-crafted features [1]. Examples of trained filters of the first convolutional layer can be seen in Fig. 2. These first-layer filters capture low spatial frequency signals. In contrast, a mixed set of low and high frequency patterns exists in the first convolutional layer shown in [5, 6]. This indicates that the essential information of this task of classifying holistic slice-based body regions lies in the low frequency spatial intensity contrasts. These automatically learned low frequency filters need no tuning by hand, which is different from using intensity histograms, e.g. [8, 9]. In-betweenconvolutional layers, the ConvNet performs max-pooling operations in order to summarize feature responses across non-overlapping neighboring pixels (see Fig. 3). This allows the ConvNet to learn features that are invariant to spatial variations of objects in the images. Feature responses after the 5th convolutional layer feed into a fully-connected neural network. This network learns how to interpret the feature responses and make anatomy-specific classifications. Our ConvNet uses a final softmax layer which provides a probability for each object class (see Fig. 3). In order to avoid overfitting, the fully-connected layers are constrained, using the “DropOut” method [10]. DropOut behaves as a regularizer when training the ConvNet by preventing co-adaptation of units in the neural network. We use an open-source implementation (cuda-convnet21 ) by Krizhevsky et al. [2, 11] which efficiently trains the ConvNet, using GPU acceleration. Further speed-ups are achieved using rectified linear units as neuron activation function instead of the traditional neuron model f(x) = tanh(x) or f(x) = (1 + e −x ) −1 in both training and evaluation [2].



Current medical image fusion methods need to break some existing difficulties: first, versatility is relatively weak, and most of it is only a minority of cases as the test object not really spread to clinical diagnosis[20,21]; second, various imaging system owe different imaging principle, the acquisition mode, format , size, quality, space and time characteristics of the image are very different, so the research in the stability and high precision automat medical image registration and fusion method is one of the difficulties; third, different imaging systems obtain different image information because of different imaging principle, so which of two or more imaging systems for image fusion can get the best results should be discussed; forth, it is difficult to say a certain criteria must be better than another in a variety of image fusion optimization criteria, especially there is the absence of an absolute perfect fusion image for reference. So the standard of objectively comparing and evaluating different methods of fusion performance needs to solve; fifth, the highest goal of image fusion is correct understanding and application of the fused image ,so how to understand and take advantage of these new comprehensive information need to prove by experiment[4].

**RESULTS AND DISCUSSION**

Image guided medical diagnosis, while calling for high precision, often depends on how accrirately various structures in the image can be claljsified. The contributions of various research technique found contributed to the development of an economical image guided medical analysis model presented (Fig. I). Our final goal is to introduce a problem space through an economic analysis algorithm to retrieve related or crossreference to similar illness in the humcngous medical dataset to support and improve patient-doctor diagnosis as well as a secondaly diagnosis parmer. Therefore, the search for a simple classification technique that suit different imaging modalities is the first step towards making image-guided diagnosis system an emerging reality. The combine classific,ation technique suitable for classifying different imaging modalities studied here has been summarize as below: Lowlevel features and te.u search capabilities: lncolporating low level features search :is well as text search for better medical databas,? management. Multi-vim object recagn,:rion: Visual properties of the images with regards to the nslevance and organization of such images. Meanii@iI cafegor-izaiion: The ak'ility to support specific task images as well as different imaging modalities images. Abilit), to model image semantics: Able to capture the semantics of different imaging modalities by classifying it accordingly.

CONCLUSION

The advancement of medical ;science has dominated the experiment on imaging for a good part of .the 20" century From fundamental imaging technique to the more advance technique we found now, imaging for medical has advance at a speed that has never been imagined before. While medical diagnosis using bare e:yes is being done for the past decade, with the growing size of the medical dataset and time-consuming diagnosis, cross-referencing IO similar illness and the study of how these images could be incorporated utilizing the big), performance computing shall give birth to a new era of liealthcare service.