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Automated disease detection on the basis of brain size using Machine learning approach

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Abstract
Machine learning analysis of neuroimaging data can accurately predict chronological size/age in healthy people and deviations from healthy brain ageing have been associated with cognitive impairment and disease. In most cases, the diagnosis of brain disorders such as epilepsy or a brain tumor is slow and requires endless visits to doctors and electroencephalogram technicians. This work aims to automate brain disorder diagnosis on the basis of brain size by using Artificial Intelligence and deep learning. There are many brain disorders can be detected by reading brain size. Using the gather dataset directly from the brain with a noninvasive procedure gives significant information about its health & disease. Classifying and detecting anomalies on this brain is what doctors currently do when reading an Electroencephalography? With the right amount of dataset and the use of machine learning models, it could be possible to learn and classify brain activity like (i.e: anxiety, epilepsy spikes, abnormal tumor activity, disease etc). Subsequently, a trained Neural Network would interpret those brain datasets and identify evidence of a disorder to automate the detection and classification of those disorders / disease found.

Keywords: Machine learning, Diagnosis, Neural Network

Introduction

Medical diagnosis aided by software systems that use a variety of artificial intelligent and machine learning algorithms have been available since early 1990s. These medical diagnostic tools use a patient's symptoms, diagnostic measurements and lab results as inputs, and the system returns a ranked list of diagnoses along with suggested treatments. Although such tools exist to diagnose a general illness, radiology does not yet have a generalized tool which can assist in diagnosis. Previous research failed to create a tool which would assist in general analysis of radiology images for several reasons that include the lack of (1) transparency of machine learning and artificial intelligence algorithms to provide feedback on which features were detected and used by the algorithm to make its diagnostic decision, (2) large, diverse, annotated, longitudinal, open-source data sets that are needed to build and train the diagnostic algorithms, (3) the massive hardware support necessary to process high fidelity 3D images and extract useful information. Recent advancements in the non-invasive, soft-tissue imaging modalities is generating large volumes of high-resolution data. Radiologists use high resolution soft tissue images to diagnose numerous medical conditions such as brain cancer, aneurysms, traumatic brain injury, and viral infections. Soft tissue scans are rich with feature information that helps the practitioner differentiate healthy tissue from the pathological cases. A variety of specialized imaging techniques is need for diagnosis of a particular brain anomaly and no single imaging technique is sufficient as a general diagnostic imaging. However, combining image sets from multiple imaging techniques can create a unique signature for each soft tissue type, producing a large number of features for post processing by a machine learning (ML) algorithm. Even a radiology specialist needs several hours to analyze multiple softtissue image sets, extract meaningful features, and integrate the partial findings to create a feature composite used to formulate a diagnosis for a single patient. Applying ML to medical images could significantly advance medicine due to an extraordinary ability to detect and classify, potentially beyond human ability. Machine learning has already been applied to brain images datasets to detect diseases such as brain tumors, brain disorders, Alzheimer's or other disease etc. So far, Support Vector Machines (SVM) have been the most popular machine learning technique among the researchers, which have been applied for e.g. for the classification of schizophrenia, Alzheimer's disease [15] and the early detection of disease [11]. Applied SVM to measures of grey matter density extracted from Capture images scans for classification of gender and obtained an accuracy of 89% [19].

Objective

- To design the diseases detection system.
- Predication of Diseases on the basis of size of brain.
- Find the preference of system on the basis of different parameter.

2. Related Work

Unfortunately, in the domain of general diagnosis the above guidelines are interpreted as trade- offs and the resulting models have either high performance but low transparency or high transparency but low performance. For example, the class of DSTs that use artificial neural network in general have good classification performance, but poor knowledge transparency when trained on a sufficiently large data set. In contrast, Assistant-R, R-QMR, ISABEL and other DSTs are top down induction engines that use decision trees and expert knowledge ontology with high transparency but the performance is often not as high (Cestnik et al., 1987; Miller, 2016; Martinez-Franco et al., 2018). Due to the high-stake consequences of making medical diagnostic decisions it is important that the proposed DST solutions meet all proposed guidelines. The quality of the machine learning algorithms for simple tasks such as medical image segmentation or classification is continuously improving. That said, few diagnostic synthesis tools exit and even fewer are actually used by the radiologist (Shattuck and Leahy, 2002; Wang et al., 2016). The adoption criteria for the bio-medical imaging tools should include (1) what is the tool's knowledge transparency and the explanation ability, (2) low type I and type II error, (3) how much new, previously unavailable information the tool discovered and presented to a physician and (4) how much integration overhead did the tool introduce or how well does the tool integrate into the exiting image processing stream. Unlike many machine learning applications, the use of computer vision algorithms as the diagnostic tools for processing brain scan images have direct impact on the patient life and wellbeing. The type II errors of falsely inferring the absence of anomaly in the brain tissue is unacceptable, while a low false positive error (type I error) is allowed as the algorithm's purpose is to aid the diagnostic process and not to replace the human radiologist. The desired efficacy of the DSTs is to have high sensitivity and specificity scores to make the error repeated on multiple trials on a single patient highly improbable – a performance comparable to a human. Currently, the segmentation of brain soft tissue using machine learning algorithms simply does not have high enough sensitivity and specificity scores to be accepted as a medical support tool (Menze et al., 2015). Although generally DSTs still lag behind physicians, Menze et al. compared the performance of a radiologist against the latest machine learning algorithms on the benchmark brain tumor image segmentation images to conclude that the error between the human and the machine for the brain tumor segmentation are comparable (Menze et al., 2015). The expected sensitivity and specificity threshold for the processing of the brain scan images is still to be determined, but the application of the bio-medical diagnostic tools in other fields of medicine commonly exceed 95% sensitivity and specificity scores, and we expect a similar or higher threshold to be applicable for any clinically relevant DST. The diagnostic process of a single case already requires several hours by a highly trained and specialized radiologist, so an introduction of a new tool has an associated costbenefit trade-off. If the balance between the increases of the radiologist's decision-making complexity exceeds the amount of the new information presented to a radiologist, the new tool hinders the diagnostic process and could lower the physician's diagnostic accuracy. For example, Kononenko's empirical studies showed that the physicians prefer the diagnosis and explanations by Bayesian classifiers and decision tree classifiers, such as the Assistant-R and LFC, due to their high knowledge transparency (Kononenko, 2001). In contrast, the top performing ML algorithms analyzing problems such as the brain tumor segmentation in the images (BraTS) or even a much easier task of recognizing and localize ordinary objects in the natural scenes using artificial neural network- based algorithms have poor knowledge transparency and explanation ability (Kononenko, 2001; Krizhevsky et al., 2012; Menze et al., 2016). The goal of AI based tools that support radiologist's analysis of brain soft tissue images is to reduce the diagnostic complexity and error while providing additional analytic insight with high knowledge transparency and explanation. The diagnostic accuracy using the ML data analysis has to be verified and compliant with the radiologist's knowledge and practice. The knowledge structure extracted from the images has to be supported by clearly identified lower level features that consist of the image artifacts already used by the radiologist, clearly identified artifacts that were not used to synthesize the extracted knowledge, or the new features not seen by the radiologists. The relationships between the features define the structure of the knowledge that can be argued by the radiologist in support of the final diagnosis. How the model learned to select the relevant features and the relationships among them does not have to mimic how the radiologists learn to diagnose a pathology as the AI's goal is to learn the complex features and interactions missed in the first place. That said, the newly discovered knowledge must be verifiable by the radiologist. Imaging tests are ordered for a variety of underlying clinical complaints1 to generate a differential diagnosis or to determine the extent or localization of a known pathology. Radiologists analyses the resulting scans with little knowledge of the patient's case other than some basic history, which helps prevent diagnostic bias. For the same reasons, we will survey only the methodologies that analyses brain scans without and do not use additional patient information as the algorithm's inputs. To further limit the scope, we will discuss the diagnosis of brain tumors and traumatic brain injury (TBI) as two brain pathologies representative of different diagnostic mechanisms.

In 2016, half of the submitted solutions for the BraTS image segmentation problem used a CNN as a feature extractor submodel within the overall ML architecture, and many of these were among the top performing algorithm implementations (Menze et al., 2016; Havaei et al., 2017). Other medical image classification problems such as lung cancer classification and brain tumor classification also commonly use the CNN as a feature extractor from 2D images and 3D composites (ElDahshan et al., 2014; Shankar et al., 2016). Many recent publications report the variations of the baseline CNN and decoupling the feature detector (CNN) from the classification models to improve the classification results on the problem domain. In particular, Haveai et al. introduced a cascaded, deep neural network architecture that explores image features in the local and global context (Havaei et al., 2017). The proposed architecture uses two- phase training to address the tumor labeling imbalance and the output of the basic CNN model is fed as an additional input into the subsequent CNN model for improved tumor segmentation accuracy. Russakovsky's survey of the scene recognition methodologies includes the side-byside algorithms comparison which concluded that the CNNs as the multi-stage, hand-tuned feature extractor followed by a discriminant classifier always outperformed the traditional feature coded or the single deep neural network architectures (Russakovsky et al., 2015). The cell image segmentation using small training and validation data was explored using multi-channel feature maps based on multi-path heuristics: the image symmetry coded the localization and the feature context was coded as the contradicting model hypothesis. The output of the proposed U-Net architecture was the segmented and annotated image that could be used as an input to a subsequent work-flow processing stream (Ronneberger et al., 2015).

3. Methodology

Below figure shows the pre-processing models, described in the previous section as tasks p to regularize the images by resizing, rotating, and removing the unwanted artifacts from the image. The soft- tissue of the brain is extracted as a region of interest (ROI) by removing all other structures from the images. The low-level feature extraction models, labeled f, generate a feature space used for the structural measurements and the learning process. The higher order features are extracted from the 3D composites or measured from the 2D images. The ability to identify and compare the higher order features requires registration of brain structures – a task where the anatomical regions of the brain are detected and labeled which allows for a measurement of structural similarities across brain structures. The similarity measures use a variety of comparative morphometry and group analysis algorithms. An accurate registration allows for the anatomical region segmentation and subsequent comparison of the region's volume against the expected. The volumetric analysis of the MRI based regional segmentation was successfully used to diagnose Autism. Finally, the visualization and 3D reconstruction are not feature extractor models, non- less they are used in parallel with the feature extractor models to verify the model's results. The last prediction in the hierarchically stacked models is the synthesis of the diagnosis that uses the input vector of the local, regional, and global feature measurements to predict the diagnosis. This high-level reasoning model can be implemented using many different methods including probabilistic models, decision-theoretic expert systems, fuzzy set theory, neural networks and ontological based reasoning. The essential quality of these high-level reasoning engines is its transparency and the ability to trace back the diagnostic decision through the ensemble of models used to support the diagnosis. Figure shows the knowledge transparency as the gray arrows that identify the key measurements that are traced to the high-level features and weights, supported by the structures in the 3D composites that lead all the way to the low-level features and image artifacts. It is worth noting that the image processing work-flow should be flexible and configurable to select the alternate processing models to diagnose different pathologies. For example, the preprocessing may or may not include image normalization, orientation, or image resizing. Feature extraction can be minimal using the pixel intensity values alone to create the feature set, or use complex spatial statistics to define the features of interest, or a combination of both. The diagnosis prediction should be agnostic of the input vector size or its composition. Creation of a transparent machine learning model aims to help practitioners find the image patterns that go unnoticed, and become a tool for an early stage disease diagnosis, a treatment monitoring, ananalysis of brain's structures, tissue or brain center segmentation, and diagnostic prediction.

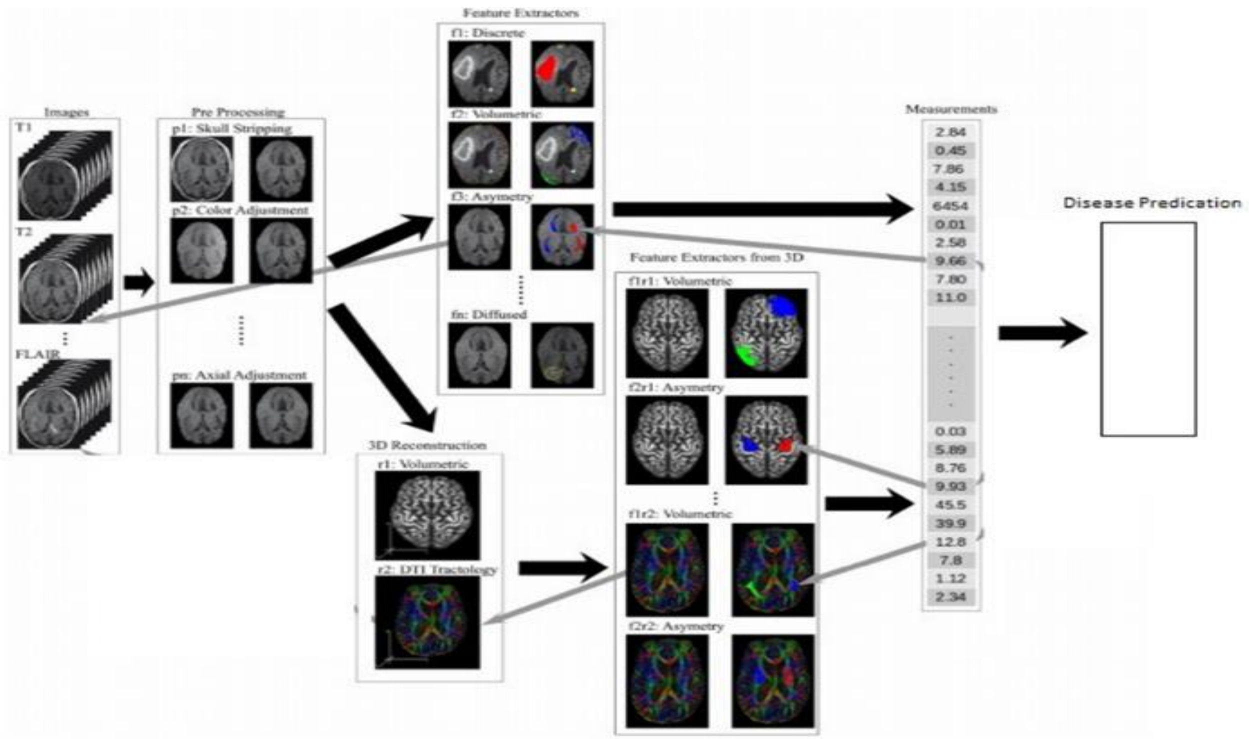


Fig 1: Convolution Neural Network (CNN) based Disease Detection

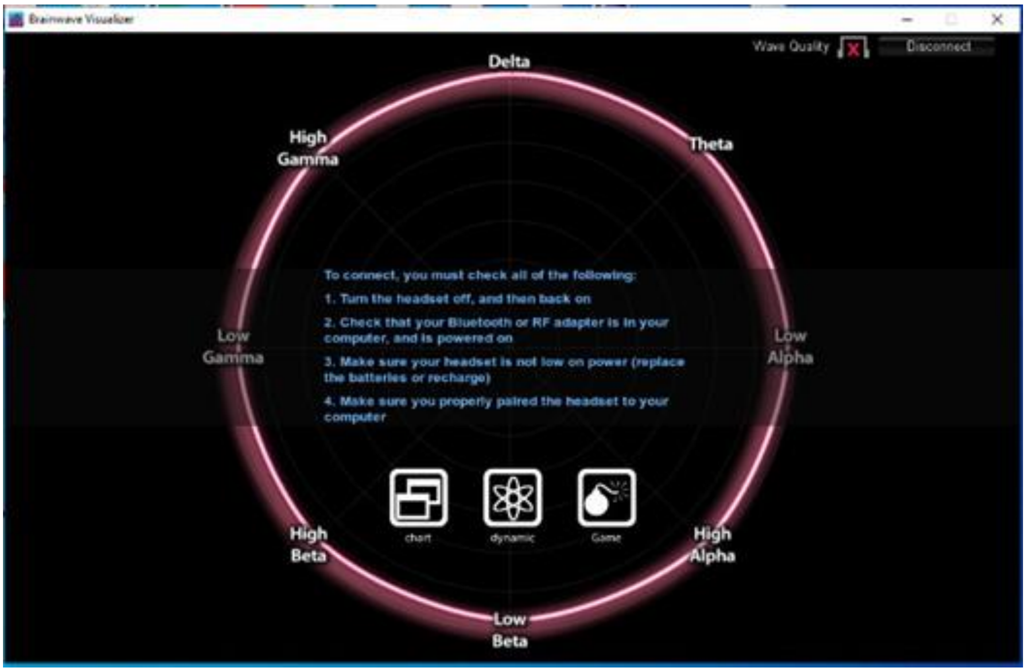
Convolution Neural Networks A convolution neural network (CNN) is an artificial neural network inspired architecture that extracts image features with increasing complexity or structure by alternating the convolution and pooling filters on the input implemented as respective neural network layers. The convolution filers can be randomly sampled from the inputs (imprinted), engineered by a human, or set at random and pruned by reinforcement during the model training. The output of the CNN architecture is either the final vector of detected features or the architecture will include the processing of the feature vector and produce the final classification through a fully connected layer (Fukushima and Miyake, 1982; Poggio and Girosi, 1990; Lo et al., 1995). ML architectures for image classification have improved significantly following the work of Krizhevsky et al. on the ImageNet visual recognition database in 2012 using a CNN (Krizhevsky et al., 2012). In 2015, the best results on the ImageNet database were achieved using the CNN and to this day no other type of architecture produced better scene classification results (Russakovsky et al., 2015; Havaei et al., 2017; Hornak, 2017). This improvement to

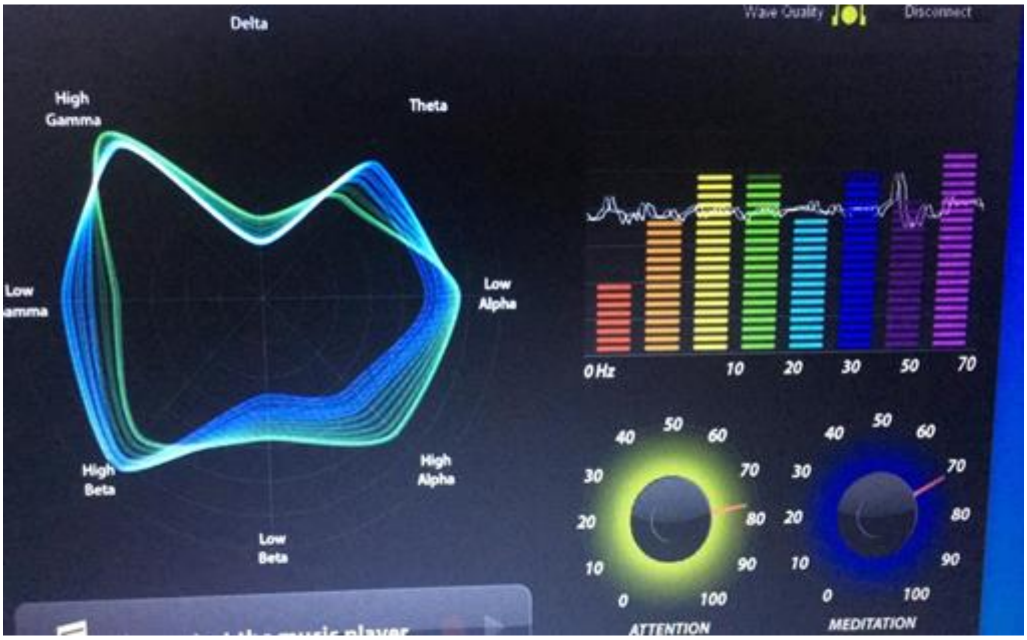
ML architectures translated to the image segmentation and classification for the medical image processing.

4. Result & Discussion

Throughout this study, we will apply classification methods to machine learning to detect disease from images & brain signals at various environmental disease induced by hipper tension. In order to quantify disease using physiological signals& brain images, a new frequency band Based approach was developed to take into account the inter-subject variances.

By using the proposed method and observing brain activity with different classification method we are observing the brain analysis. The following figure shows the stress level of person after observing the overall brain signal with images,





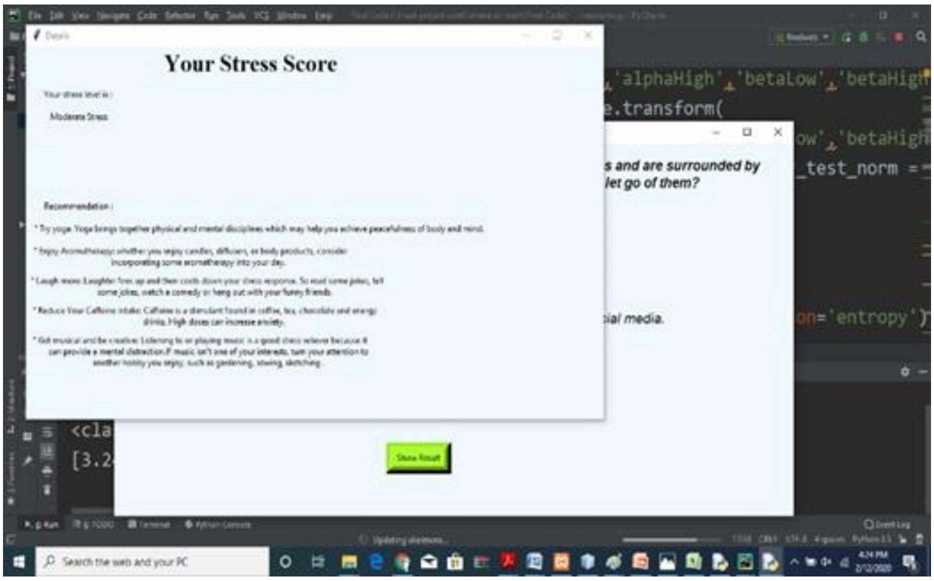


Fig 2: By considering Brain images & signal find thestress diseaseusing ML

Model of Predication

Below figure give the details of Proposed model where we had trained 80% dataset after tranining give to 80% data from sample dataset we are using 20% data set for testing and observed the result with some stander assumation those we have considered and predict the model working. From that it show Proposed model give good prdication in less time peroid. Details predication shows in following figure.

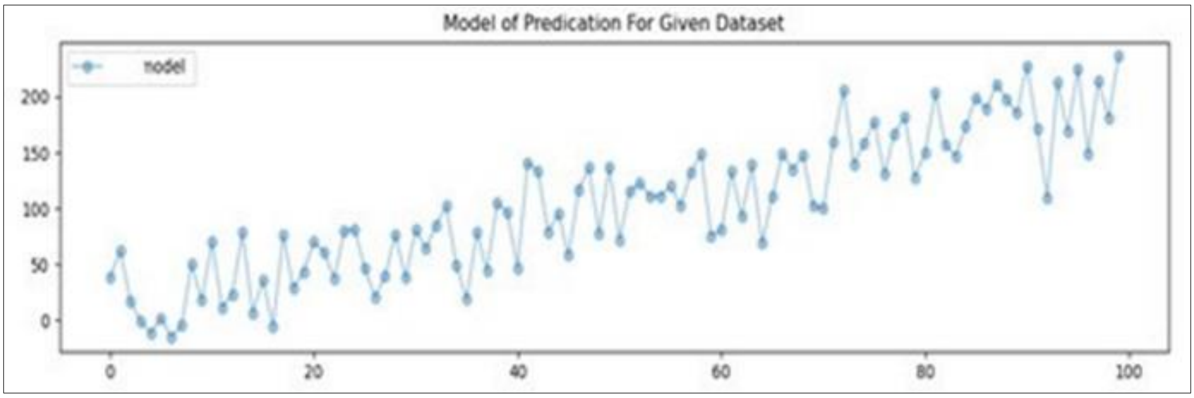


Fig 3: Model of predication of given dataset

5. Conclusion

While still in its initial stages, the application of ML in neuroimaging has shown promising results and has the potential of leading to fundamental advances in the search for imaging-based biomarkers of disorders detection using Images. Nevertheless, several improvements will be required before the full potential of ML in neuroimaging can be achieved. Firstly, given the complexity of ML models, we need to move away from studies with small to modest sample sizes in favour of simple images. A possible way of achieving this is through multicenter collaborations, in which data is collected using the same recruitment criteria and scanning protocols across sites. A further way of increasing the sample size is through multi-site data sharing initiatives. Secondly, the integration of CNN and recurrent neural networks is likely to lead to significant advances in ML in the next few years. In neuroimaging, this integration could be particularly useful for analyzing fMRI data.

In conclusion, the capacity of ML models to learn complex and abstract representations through nonlinear transformations, makes this a promising approach to single subject prediction in imaging. While there are still important challenges to overcome, the findings reviewed here provide preliminary evidence supporting the potential role of ML.It is observed that, in general, CNN-based techniques outperformed conventional handcrafted techniques with the limitation of requiring more training samples to achieve the optimal performance.

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