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Automatic Speech Analysis for Detection Of Dementia Using Machine Learning-A Survey

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Abstract- Machine learning has shown promise for automatic detection of Dementia disease through speech; however, efforts are hampered by a scarcity of data, especially in languages in English. In this paper , we give a description of the Machine Learning, speakers with Dementia, which is part of AphasiaBank but has not been described before in the literature. Next, we propose a method to classify dementia in, by combining the Machine Learning with Dementia Bank. This method extracts lexicosyntactic features independently in the two languages, and then learns a correspondence between the features using a large parallel corpus of out-of-domain movie dialogue data. We demonstrate that our method outperforms both unilingual and machine translation-based baselines. The goal of the study we present here was twofold. First, we sought to find acoustic (temporal) parameters that have a high correlation with MCI. For this, our starting point was our earlier study, where we examined the speech of Dementia patients [7]. There we compared the articulation rate, speech tempo, hesitation ratio, and rate of grammatical errors of dementia patients versus a normal control group. Our results showed that these acoustic parameters may have a diagnostic value for mild-stage dementia and thus can be viewed as acoustic biomarkers of dementia.

Keywords- spontaneous speech, diagnosis, acoustic analysis, temporal features, speech recognition, machine learning

I. INTRODUCTION

Dementia is a clinical syndrome with progressive deterioration in cognitive and social function and the ability to live independently, due to progressive neurodegeneration. Dementia is an umbrella term referring to Neurocognitive Disorder (NCD) and DSM-5 criteria divide this into major (dementia) and minor (Prodromal Disease or Mild Cognitive Disorder) NCD (6). Dementia most often affects older people, although young patients who receive the diagnosis early in life require special attention. Cognition refers to thinking and related processes and according to DSM-5 there are six cognitive domains that could be affected in both major and minor NCD:

- Complex attention (involving attention and information processing speed)
- Executive ability (planning, decision making, working memory)
- Learning and memory
- Language
- Perceptual - motor - visual perception/praxis
- Social cognition (recognition of emotions and behavioral regulation, social appropriateness)

According to DSM-5 dementia (major NCD) is defined by the following:

There is evidence of substantial cognitive decline from a previous level of performance in one or more of the domains listed above, based on the concerns of the individual, a knowledgeable informant, or the clinician; and a decline in neurocognitive performance, typically involving test performance in

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the range of two or more standard deviations below appropriate norms

The cognitive deficits are sufficient to interfere with independence and activities of daily living (ADL)

- The cognitive deficits are not in the context of delirium and not primarily attributable to another mental disorder.

Dementia divides into three groups depending on the severity of the decline in cognitive and functional ability: mild, moderate and severe.

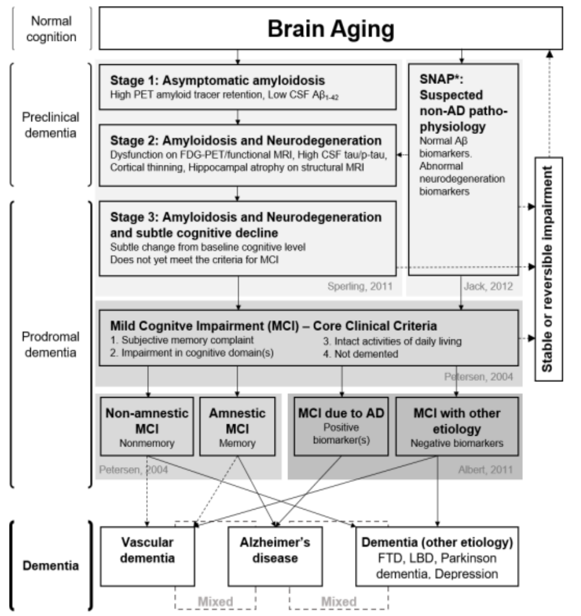

Figure 1: Overview of the cognitive stages from normal cognition to dementia.

The overview is based on the diagnostic criteria for preclinical dementia suggested by Sperling et al. [11] and the core clinical criteria for mild cognitive impairment suggested by Petersen et al.[13] Dementia is a syndrome that describes a wide range of symptoms that occur when the brain is affected by certain conditions. Dementia can be grouped in reversible and irreversible dementia disorders. The reversible dementia disorders are most often drug induced, caused by hormonal imbalance or vitamin deficiencies and are out of scope in this paper . The irreversible dementia disorders are progressive, degenerative disorders that are affecting memory and other cognitive functions to the extent that they interfere with a person's daily life and activities. The most common types of irreversible dementia include Alzheimer's disease (AD), vascular dementia (VaD) and mixed dementia, particularly the combination of AD and VaD.

Cognitive impairment is used as a broad term describing impairment in any one (or all) of the cognitive domains assessed by objective cognitive performance irrespective of the underlying cause. This paper deals with cognitive impairment and all-cause dementia in general and the major types of dementia including AD, VaD and other/unspecified dementias (OD). The following sections will describe the causes, symptoms and underlying mechanisms of the dementia disorders, with emphasis on AD. Dementia, a threat to Global Health and Aging Advances in medicine and socioeconomic development have made one of humanity's greatest achievements, namely: prolonged longevity [1]. The rise in life expectancy accompanied by declining fertility rates is now driving an epidemiological transition increasing the proportion of older people in the total population.

In Europe alone, the elderly population (>65 years) is estimated to double from 88 to 153 million by 2060 and the fastest growing segment of the population will be those aged 80 and older tripling in number from 24 to 60 million [2]. This demographic shift is associated with increased prevalence of chronic diseases and as it is also accompanied by prolonged survival, it will put a large pressure on healthcare systems [3]. Maintaining a healthy life is therefore of outmost importance. While women outlive men on average, they have poorer health status [4,5] and this clearly justifies an increased focus on ageing, specifically of women. One of the most daunting and costly consequences of ever-longer life expectancies is dementia.

Dementia and cognitive impairment are by far the leading causes of disability and in particularly need for care among older people worldwide, thus it has been estimated that the health and social care costs for dementia exceed costs of other chronic diseases like cancer, cardiovascular disease and stroke [6]. Unfortunately, there has been much less investment in dementia research, given its burden, compared with research in cancer and cardiovascular disease. In Denmark, women account for more than 2/3 of the total number of people living with dementia [7], and dementia is the second leading cause of death in women [8].

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Nosology of Dementia Disorders

Diagnosis and Classification

The concept of dementia and its classification has developed on the basis of accumulating evidence of clinicopathological entities and presumed etiological factors. Two major diagnostic classification systems exist and are used for diagnosis of dementia. The WHO's International Classification of Diseases and Related Health Problems 10th Revision (ICD-10) and the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (DSM 5).

Further, the National Institute on Aging and the Alzheimer's Association (NIA-AA) proposed new diagnostic criteria for dementia, AD and mild cognitive impairment (MCI) in 2011 [9,10], and a working group also proposed diagnostic criteria for preclinical AD. Preclinical AD refers to an early disease stage where pathological changes in the brain can be detected using biomarkers [11]. Alongside the NIA-AA also an International Working Group proposed similar research diagnostic criteria for AD. Like the NIA-AA criteria it defines three stages of AD: preclinical AD, prodromal AD (MCI due to AD in the NIA-AA criteria) and AD dementia [12]. There are differences on how the stages are conceptualized however this will not be elaborated any further in this paper . The diagnostic guidelines outline several cognitive stages ranging from normal cognition to dementia, as illustrated in figure 1.

The clinical diagnosis of dementia is based on the medical history, a neuropsychological test battery and a thorough clinical examination of symptoms. In addition, there are certain imaging biomarkers such as computed tomography (CT), magnetic resonance imaging (MRI), single photon emission computed tomography (SPECT), positron emission tomography (PET) andcerebral spinal fluid (CSF) biomarkers that may be used to support the clinical diagnosis [9]. These techniques are however mainly used in specialized clinics and for research purposes rather than in general practice. Detection of neuropathological lesions in the brain by autopsy is the gold standard for the diagnosis of dementia-related diseases [16].

Table 1: Overview of main dementia subtypes. The table was made with inspiration from [19]

	Subtypes of dementia			
	Alzheimer's Disease	Vascular Dementia	Lewy Body Dementia	Frontotemporal Dementia
Onset	Gradual	Acute or gradual	Insidious	Early Insidious
Progression	Gradual	Stepwise or gradual	Fluctuating	Rapid
Signs and Symptoms	Memory loss, language deficits, mood and personality changes	Memory loss, language deficits, dysarthria, emotional lability, decreased concentration	Depression, hallucinations, variability in terms of day to day symptoms	Poor judgement, social withdrawal, inappropriate behaviour
Regions of atrophy	General atrophy noted in the medial temporal lobe	Strokes, lacunar infarcts, white matter lesions	Generalized atrophy throughout	Frontal and temporal lobes
Pathologic features	Amyloid plaques Neurofibrillary tangles	Cerebrovascular disease	Lewy bodies	Pick bodies

II.BACKGROUND AND RELATED WORK

Dementia disease and language Dementia disease is a neurodegenerative disease affecting 5.7 million people in the US in 2018, and 1 in 10 people over the age of 65. It is the most financially costly disease in the American healthcare system today; the cost is expected to further increase since the population of Americans over age 65 is projected to grow from 53 million today to 88 million in 2050 (Dementia Association, 2018). Dementia is a symptom of DEMENTIA , characterized by a long-term decline in memory and cognitive ability. Although no cure currently exists for DEMENTIA , early detection and intervention is crucial to mitigate the effects of Dementia (Dubois et al., 2016). Language deterioration and speech impairment are some of the earliest symptoms of DEMENTIA .

In particular, patients with DEMENTIA have difficulty finding words for specific objects. This lends itself to reliable cognitive tests for DEMENTIA detection. For example, category and letter fluency tasks, where the subject names as many objects in a certain category or starting with a certain letter in 60 seconds, reliably differentiates between DEMENTIA patients and healthy controls (Monsch et al., 1992). The Mini Mental State Examination (MMSE) is a popular test in which the subject is given a battery of cognitive tests and is scored on a range from 0 to 25 (Folstein et al., 1983). Connected speech is another reliable method of detecting DEMENTIA , since patients with DEMENTIA have been shown to exhibit differences in word frequency, syntactic complexity, idea density, and pause frequency and duration (Taler and Phillips, 2008; Roark et al., 2011). A popular task for eliciting connected speech is the Cookie Theft picture description task from the

Boston Diagnostic Aphasia Examination (Goodglass and Kaplan, 1983). In this task, the subject is shown the picture in Figure 2.1 and is asked to describe it in as much detail as possible.

Machine Learning For Detection Of Dementia

Computerized analysis combined with machine learning is effective for working with continuous speech because computers can quickly extract a wide variety of features that would be extremely time-consuming to extract manually. Fraser et al. (2016) extracted 370 acoustic, syntactic, and semantic features such as part-of-speech ratios, vocabulary richness, and MFCC coefficients; using a logistic regression classifier, their model achieved about 82% accuracy in distinguishing between DEMENTIA patients and healthy controls.

It was trained on 473 samples from Dementia Bank (Boller and Becker, 2005), using audio recordings and manual transcripts of the Cookie Theft picture description task. These results have been further refined in subsequent work. Yancheva and Rudzicz (2016) used topic models to automatically identify clusters of content words like cookie and mother, which were specified manually by Fraser et al. (2016). Zhou et al. (2016) investigated the possibility of replacing manual transcripts with automatic speech recognition (ASR). Karlekar et al. (2018) used deep neural networks like CNNs and LSTMs to achieve state-of-the-art classification accuracy on the Dementia Bank dataset. Computerized analysis of Dementia has also been applied to written text, for example, to detect signs of Dementia in the works of three British novelists (Le et al., 2011).

Multilingual Effects Of Dementia

The linguistic effects of DEMENTIA has been studied in numerous languages, such as ,(Lai et al., 2009; Lai, 2014), Japanese (Shibata et al., 2016), Koreaen (Kim et al., 2006), Portuguese (Alu´ısio et al., 2016), French (Troger et al., 2017), and Hebrew (Kav ¨ e and Levy, 2003). However, most of these studies focused on the linguistic´ characteristics of DEMENTIA , rather than machine learning methods to detect DEMENTIA through speech.

Fraser et al. (2019) used multilingual topic models in English and Swedish to detect mild cognitive impairment (MCI), but so far, very little work has been done on multilingual Dementia detection. In Mandarin Chinese, Lai et al. (2009) analyzed the speech of 62 patients performing the Cookie Theft picture description task, and found syntactic differences among speakers with DEMENTIA. A subsequent study found differences in discourse patterns (Lai, 2014). However, in both studies, features were coded manually by trained linguists. Chinese grammar is very different from most Indo-European languages: for example, it lacks verb tenses and all inflectional morphology, and has a system of noun classifiers (Chao, 1965). These differences pose unique challenges to studies of cognitive decline in Chinese. When studying grammaticality tests for aphasic patients, Lu et al. (2000) found that the free word order and simple morphology in Chinese mDementiae it difficult to construct sentences that were definitively ungrammatical.

Methods For Domain Dementia Aptation

One of the biggest challenges for using machine learning to detect Dementia is the sparsity of datasets. This is especially true for non-English languages, where clinical studies involving Dementia consist of less than 100 people. Domain Dementia aptation (e.g., transfer learning) methods aim to learn from a small dataset by combining it with a much larger dataset from a different domain, for example, data from English speakers with Dementia , or normative speech. This is a promising direction of research for multilingual Dementia detection. Daume III (2007) proposed a simple way of combining features in different domains, assuming that the same features are extracted in each domain. In this method, given data points in domains S and T, we augment the feature space with three copies of each feature, one copy specific to domain S, one copy specific to domain T, and a third copy common to both domains. Formally, the function ΦS transforms a vector xS in the source domain S, as defined by the formula: ΦS(xS) = hxS, xS, 0i. Similarly, the function ΦT transforms a vector xT in the target domain T: ΦT (xT) = hxT , 0, xT i. A classifier is then trained on the combined dataset using a standard classification algorithm. Although simple and straightforward, this method is limited to situations where the same features may be extracted in each domain. In multilingual NLP, this is unreasonably restrictive because languages may be very different from each other.

Duan et al. (2012) proposed an extension to this method to train a classifier jointly on two domains with different features in each domain, by learning projections to a common subspace. That is, ΦS(xS) = hPxS, xS, 0i, ΦT (xT) = hQxT , 0, xT i, where P and Q are projection matrices learned from data. Domain Dementia aptation and multi-task learning have been applied to automatic classification of DEMENTIA as well. Noorian et al. (2017) improved the classification accuracy on Dementia Bank by augmenting it with a larger corpus of normative speech data. Pou-Prom and Rudzicz (2018) applied generalized canonical correlation analysis (GCCA) to combine picture description, category fluency, letter fluency, and demographic data to generate a multiview embedding for downstream classification. Zhu et al. (2018) proposed transductive consensus networks (TCNs) to generate similar interpretations of different modalities; on Dementia Bank, they treated acoustic, syntactic, and lexical features as three separate modalities. Masrani et al. (2017) detected mild cognitive impairment (MCI) in Dementia Bank by applying domain Dementia aptation techniques to augment the MCI group with the much larger DEMENTIA group from the same dataset. In this paper, we propose a new method of domain Dementia aptation across different languages. This method learns a correspondence between feature spaces using a large bilingual parallel corpus. This appears to be the first study that transfers domains in detecting cognitive decline.

III.RELATED WORK

The Several applications mentioned earlier suggests considerable Dementia vancementso far in ML algorithms and their fundamental theory. The discipline is divulging in several direction, probing a range of learning problems. ML is a vast discipline and over past few Dementia es numerous researchers have Dementia ded their works in this field. The enumeration of these works is countably infinite and mentioning every work is out of the scope of this paper. Howeverthis paper describes the main research questions that are being pursued at present and provide references tosome of the recent notable works on that task.

1. Using Unlabelled Data In Supervised Learning [10][11][25][25][25] Supervised learning algorithms approximate the relation between features and labels by defining an estimator f : X → Y for a particular group of pre-labeled training data {xi , yi}. The main challenge in this approach is pre-label data is not always re Dementiaily available. So before applying Supervised Classification, data need to be preprocessed, filtered and labeled using unsupervised learning, feature extraction, dimensionality reduction etc. there by Dementia ding to the total cost. This hike in cost can be reduced effectively if the Supervised algorithm can make use of unlabelled data (e.g., images) as well. Interestingly, in many special instances of learning problems with Dementia ditional assumptions, unlabelled data can indeed be warranted to improve the expected accuracy of supervised learning. Like,consider classifying web pages or detecting spam emails. Currently active researchers are seriously taking into account new algorithms or new learning problems to exploit unlabelled data efficiently.

2. Transferring the Learning Experience [12][13][14][15][16] In many real life problem, the supervised algorithm may involve learning a family of related functions (e.g., diagnosis functions for hospitals across the globe) rather than a single function. Even if the diagnosis functions for different cities (e.g., Kolkata and London) are presumed to be relatively different, some commonalities are anticipated as well. ML algorithms like hierarchical Bayesian methods give one approach that assumes the learning parameters of both the functions, say for Kolkata and London respectively, have some common prior probabilities, and allows the data from different city hospitals to over rulerelevant priors as fitting. The subtlety further increases when the transfer among the functions are compounded.

3. Linking Different Ml Algorithms Various ML algorithms have been introduced and experimented on in a number of domains. One trail of research aims to discover thepossible correlations among the existing ML algorithms, and appropriate case or scenarios to use a particular algorithm. Consider, theses two supervised classification algorithms, Naive Bayes and Logistic Regression. Both of them approach many data sets distinctly, but their equivalence can be demonstrated when implemented to specific types of training data (i.e., when the criteria of Naive Bayes classifier are fulfilled, and the number of examples in trying set tends to infinity). In general, the conceptual understanding of ML algorithms, their convergence features, and their respective effectiveness and limitations to date remain Dementia cal research concern.

4. Best Strategical Approach For Learners Which Collects Their Own Data A border research discipline focuses on learning systems that insteDementia of mechanically using data collected by some other means, actively collects data for its own processing and learning. The research is devoted into finding the most effective strategy to completely hand over the control to the learning algorithm. For example consider a drug testing systemwhich try to learn the success of the drug while monitoring the exposed patients for possible unknown side effects and try to in turn minimising them.

5. **Privacy Preserving Data Mining** [17][18][19][20] This approach involves successfully applying data mining and obtaining results without exploiting the underlying information is attracting variety of research communities and beyond. Consider, a medical diagnosis routine trained with data from hospitals all over the world. But due to privacy concerns, this kind of applications is not largely pursued. Even if this presents a cross roDementia between data mining and data privacy, ongoing research says a system can have both. One proposed solution of the above problem is to develop a shared learning algorithm inste Dementia of a central database. Each of the hospitals will only be allowed to employ the algorithm under pre-defined restrictions to protect the privacy of the patients and then hand it over to the next. This is an booming research domain, combining statistical exploitation of data and recent cryptographic techniques to ensure data privacy.

F. Never-Ending Learners[21][22][23][24] Most of the machine learning tasks entails training the learner using certain data sets, then setting aside the learner and utilise the output. Whereas, learning in humans and other animals learn continuously, Dementia apting different skills in succession with experience, and use these learnings and abilities in a thoroughly synergistic way.Despite of sizeable commercial applications of ML algorithms, learning in machines(computers)to date has remained striking lylacking compared to learning in human or animal. An alternative approach that more diligently capture the multiplicity, Dementia eptness and accumulating character of learning in human, is named as never- ending learning. For instance, the Never Ending Language Learner (NELL)[8] is a learner whose function is learning to re Dementia web pages and has been reported toreDementia the world wide web every hour since January 2010. NELL has obtainedalmost 80 million confidence- weighted opinions (Example, servedWith(tea, biscuits)) and has been able to learn million pairs of features and parameters that capacitate it to acquire these beliefs. Furthermore, it has become competent in reDementiaing (extracting) more beliefs, and overthrow oldinaccurateones, Dementia ding to a collection of confidence and provenance for each belief and there by improving each day than the last.

Categorization of Ml Algorithms

An overwhelming number of ML algorithms have been designed and introduced over past years. Not everyone of them are widely known. Some of them did not satisfy or solve the problem, so another was introduced in its place. Here the algorithms are bro Dementialy grouped into two category and those two groups are further sub-divided. This section try to name most popular ML algorithms and the next section compares three most widely used ML algorithms. A. GROUP BY LEARNING STYLE

1. **Supervised learning** — Input data or training data has a pre-determined label e.g. True/False, Positive/Negative, Spam/Not Spam etc. A function or a classifier is built and trained to predict the label of test data. The classifier is properly tuned (parameter values are Dementia justed) to achieve a suitable level of accuracy.

2. Unsupervised learning - Input data or training data is not labelled. A classifier is designed by deducing existing patterns or cluster in the training datasets.

3. **Semi-supervised learning** - Training dataset contains both labeled and unlabelled data. The classifier is train to learn the patterns to classify and label the data as well as to predict.

4. Reinforcement learning - The algorithm is trained to map action to situation so that the reward or feedback signal is maximized. The classifier is not programmed directly to choose the action, but inste Dementia trained to find the most rewarding actions by trial and error.

5. Transduction --- Though it shares similar traits with supervise learning, but it does not develop a explicit classifier. It attempts to predict the output based on training data, training label, and test data.

6. Learning to learn --- The classifier is trained to learn from the bias it induced during previous stages.

7. It is necessary and efficient to organise the ML algorithms with respect to learning methods when one need to consider the significance of the training data and choose the classification rule that provide the greater level of accuracy.

B. ALGORITHMS GROUPED BY SIMILARITY

1. **Regression Algorithm**s Regression analysis is part of predictive analytics and exploits the co-relation between dependent (target) and independent variables. The notable regression models are:Linear Regression, Logistic Regression, Stepwise Regression , Ordinary Least Squares Regression (OLSR), Multivariate Dementia aptive Regression Splines (MARS) , Locally Estimated Scatterplot Smoothing (LOESS) etc.

2. Instance-based Algorithms Instance-based or memory-based learning model stores instances of training data inste Dementia of developing an precise definition of target function. Whenever a new problem or example is encountered, it is examined in accordance with the stored instances in order to determine or predict the target function value.It can simply replace a stored instance by a new one if that is a better fit than the former. Due to this, they are also known as winner-take-all method. Examples: K-Nearest Neighbour (KNN), Learning Vector Quantisation (LVQ), Self-Organising Map (SOM), Locally Weighted Learning (LWL) etc.

3. **Regularisation Algorithm** Regularisation is simply the process of counteracting overfitting or abate the outliers. Regularisation is just a simple yet powerful modification that is augmented with other existing ML models typically Regressive Models. It smoothes up the regression line by castigatingany bent of the curve that tries to match the outliers. Examples: Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO) , Elastic Net, Least-Angle Regression (LARS) etc.

4. Decision Tree Algorithms A decision tree constructs atree like structure involving of possible solutions to a problem based on certain constraints. It is so namedfor it begins with a single simple decision or root, which then forks off into a number of branches until a decision or prediction is mDementiae, forming a tree. They are favoured for its ability to formalise the problem in hand process that in turn helps identifying potential solutions faster and more accurately than others. Examples: Classification and Regression Tree (CART), Iterative Dichotomiser 3 (ID3), C4.5 and C5.0, Chi-squared AutomaticInteraction Detection (CHAID) , Decision Stump, M5, Conditional Decision Trees etc.

5. **Bayesian Algorithms** A group of ML algorithms employ Bayes' Theorem to solve classification and regression problems. Examples:Naive Bayes, Gaussian Naive Bayes, Multinomial Naive Bayes, Averaged One-Dependence Estimators (AODE), Bayesian Belief Network (BBN), Bayesian Network (BN) etc.

6. **Support Vector Machine** (SVM) SVM is so popular a ML technique that it can be a group of its own. It uses a separating hyper plane or a decision plane to demarcate decision boundaries among a set of data points classified with different labels. It is a strictly supervised classification algorithm. In other words, the algorithm develops an optimal hyper plane utilising input data or training data and this decision plane in turns categories new examples. Based on the kernel in use, SVM can perform both linear and nonlinear classification.

7. Clustering Algorithms Clustering is concerned with using ingrained pattern in datasets to classify and label the data accordingly.Examples:K-Means, K-Medians, Affinity Propagation, Spectral Clustering, Ward hierarchical clustering, Agglomerative clustering. DBSCAN, Gaussian Mixtures, Birch, Mean Shift, Expectation Maximisation (EM) etc.

8. Association Rule Learning Algorithms Association rules help discover correlation between apparently unassociated data. They are widely used by ecommerce websites to predict customer behaviors and future needs to promote certain appealing products to him. Examples: Apriori algorithm, Eclat algorithm etc.

9. **Artificial Neural Network** (ANN) Algorithms A model based on the built and operations of actual neural networks of humans or animals.ANNs are regarded as non-linear modelsas it tries to discover complex associations between input and output data. But it draws sample from data rather than considering the entire set and thereby reducing cost and time. Examples: Perceptron, BackPropagation, Hop-field Network, RDementiaial Basis Function Network (RBFN) etc.

10. **Deep Learning Algorithms** These are more modernised versions of ANNs that capitalise on the profuse supply of data today. They are utiliseslarger neural networks to solve semi-supervised problems where major portion of an abound data is unlabelled or not classified. Examples: Deep Boltzmann Machine (DBM), Deep Belief Networks (DBN), Convolutional Neural Network (CNN), Stacked Auto-Encoders etc.

11. **Dimensionality Reduction Algorithms** Dimensionality reduction is typically employed to

reduce a larger data set to its most discriminative components to contain relevant information and describe itwith fewer features. This gives a proper visualisation for data with numerous features or of high dimensionality and helps in implementing supervised classification more efficiently.Examples: Principal Component Analysis (PCA), Principal Component Regression (PCR), Partial Least Squares Regression (PLSR), Sammon Mapping, Multidimensional Scaling (MDS), Projection Pursuit, Linear Discriminant Analysis (LDA), Mixture Discriminant Analysis (MDA), QuDementiaratic Discriminant Analysis (QDA), Flexible Discriminant Analysis (FDA) etc

12. **Ensemble Algorithms** The main purpose of an ensemble method is to integrate the projections of several weaker estimators that are singly trained in order to boost up or enhance generalisability or robustness over a single estimator. The types of learners and the means to incorporate them is carefully chosen as to maximise the accuracy. Examples: Boosting, Bootstrapped Aggregation (Bagging), Dementia aBoost, Stacked Generalisation (blending), GrDementiaBoosting Machines (GBM), GrDementiaient Boosted Regression Trees (GBRT), Random Forest, Extremely Randomised Trees etc.

Measuring and comparing performances of popular ml algorithms

Though various researchers have contributed to ML and numerous algorithms and techniques have been introduced as mentioned earlier, if it is closely studied most of the practical ML approach includes three main supervised algorithm or their variant. These three are namely, Naive Bayes, Support Vector Machine and Decision Tree. Majority of researchers have utilised the concept of these three, be it directly or with a boosting algorithm to enhance the efficiency further. These three algorithms are discussed briefly in the following section.

1. **Naive Bayes Classifier** It is a supervised classification method developed using Bayes' Theorem of conditional probability with a 'Naive' assumption that every pair of feature is mutually independent. That is, in simpler words, presence of a feature is not effected by presence of another by any means. Irrespective of this over-simplified assumption, NB classifiers performed quite well in many practical situations, like in text classification and spam detection. Only a small amount of training data is needto estimate certain parameters. Beside, NB classifiershave considerably outperformed even highly Dementia vanced classification techniques.

2. **Support Vector Machine Svm**, another supervised classification algorithm proposed by Vapnik in 1960s have recently attracted an major attention of researchers. The simple geometrical explanationof this approach involves determining an optimal separating plane or hyper plane that separates the two classes or clusters of data points justly and is equidistant from both of them. SVM was defined at first for linear distribution of data points. Later, the kernel function was introduced to tackle nonlinear data's as well.

3. **Decision Tree** A classification tree, popularly known as decision tree is one of the most successful supervised learning algorithm. It constructs a graph or tree that employs branching technique to demonstrate every probable result of a decision. In a decision tree representation, every internal node tests a feature, each branch corresponds to outcome of the parent node and every leaf finally assigns the class label. To classify an instance, a top-down approach is applied starting at the root of the tree. For a certain feature or node, the branch concurring to the value of the data point for that attribute is considered till a leaf is reached or a label is decided. Now, the performances of these three were roughly compared using a set of tweets with labels positive, negative and neutral. The raw tweets were taken from Sentiment140 data set. Then those are pre-processed and labeled using a python program. Each of these classifier were exposed to same data. Same algorithm of feature selection, dimensionality reduction and k-fold validation were employed in each cases. The algorithms were compared based on the training time, prediction time and accuracy of the prediction. The experimental result is given below .

Table 2: Comparison of Various algorithm according to time

Algorithm	Training Time (In sec.)	Prediction Time (In sec.)	Accuracy
Naïve Bayes (Gaussian)	2.708	0.328	0.692
SVM	6.485	2.054	0.6565
Decision Tree	454.609	0.063	0.69

Method	Feature Set	Acc.	Prec.	Recall (Sens.)	Spec.	F_1	AUC
Naive Bayes	Manual	61.9%	72.2%	54.2%	72.2%	61.9%	70.8%
	Automatic	58.3%	71.0%	45.8%	75.0%	55.7%	62.9%
Random Forest	Manual	67.9%	69.1%	79.2%	52.8%	73.8%	68.2%
	Automatic	71.4%	73.1%	79.2%	61.1%	76.0%	69.9%
SVM	Manual	71.4%	75.0%	75.0%	66.7%	75.0%	70.8%
	Automatic	64.3%	66.1%	77.1%	47.2%	71.2%	62.2%

Table 3: Comparison of Various algorithm according to Accuracy

Comparing the two feature sets, the best accuracy scores attained (with Random Forest for the automatic features, and with SVM for the manual features) are equivalent (71.4%), and the F_1-score with the automatic features is slightly better (76.0% *vs.* 75.0%). The fact that the F_1-scores and accuracy scores achieved with the automatically extracted feature set are competitive with the scores of the manually calculated features demonstrates that our approach of using ASR techniques for feature extraction is viable.

Comparing the precision and recall values, the Random Forest method shows a clear preference for the automatic feature set, as the recall values are the same, while the precision is higher. The case of SVM is not that clear as it gives a higher recall for the automatic features set, and a higher precision for the manual set. In this case the ROC curve is worth examining, as it allows the evaluation of a classifier at various true and false positive rates. The ROC curves of the three classifiers. In the case of the Naive Bayes classifier, the automatic feature set is worse than the manual one in almost all cases, and this fact is also clearly reflected by the corresponding AUC value in Table **1**1. However, none of the curves have a clear dominance in the case of the SVM and the Random Forest classifiers, and the best AUC values are also very close (70.8% for the manual and 69.9% for the automatic feature set).

Dementia Ai Applications Overview

- The majority of AI use-cases for predicting Dementia appear to fall into four major categories:

  Speech Monitoring: Companies are using machine learning to analyze speech patterns to detect and monitor Dementia progression.
- **Medical Image Analysis**: Companies are developing software using machine learning to analyze brain deterioration from scans to help predict the onset of Dementia .
- **Visual Indicators**: Companies are training algorithms to assess eye movement patterns to track and correlate cognitive function and brain activity.
- **Genetic Analysis:** Companies are using machine learning to analyze genetic data to predict the onset of Dementia .

IV.CONCLUSION

Current methods of assessing Dementia involve structured interviews that attempt to capture the complex nature of deficits suffered. One of the most significant areas affected by the disease is the capacity for functional communication as linguistic skills break down. These methods often do note capture the true nature of language deficits in spontaneous speech. We Dementia dress this issue by exploring novel automatic and objective methods for diagnosing patients through analysis of spontaneous speech. We detail several lexical approaches to the problem of detecting. The approaches explored rely on character n-gram-based techniques, shown recently to perform successfully in a different, but related task of automatic authorship attribution. We also explore the correlation of usage frequency of different parts of speech. We achieve a high 70% accuracy of detecting Dementia when compared with a control group, and we achieve 70% accuracy in rating Dementia in two classes, and 50% accuracy in rating Dementia into four classes. Our results show that purely computational solutions offer a viable alternative to standard approaches to diagnosing the level of impairment in patients. These results are significant step forward toward automatic and objective means to identifying early symptoms of Dementia

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