ALZHEIMER'S DISEASE PREDICTION USING VOICE ANALYSIS

A PROJECT WORK REPORT

Submitted by:

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in partial fulfillment for the award of the degree

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BONAFIDE CERTIFICATE

16CS270– PROJECT WORK

Certified that this Project Work Report **"Alzheimer's Disease Prediction Using Voice Analysis"** is the bonafide work of "**Ayush Dutta, Shailesh Kumar Jha,Vivek Kumar Sah Teli"** who carried out the project under my supervision.

SIGNATURE	**SIGNATURE**
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Submitted for the Project Work Viva-Voice Presentation held on____________

INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION

We affirm that the Project work titled **“AlZHEIMER’S DISEASE PREDICTION USING VOICE ANALYSIS”** being submitted in partial fulfillment for the award of Bachelor of Engineering is the original work carried out by us. It has not formed the part of any other project work submitted for award of any degree or diploma, either in this or any other University.

(Signature of the Candidates)

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I certify that the declaration made above by the candidates is true.

(Signature of the Guide)

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ABSTRACT

Alzheimer's Disease Prediction Using Voice Analysis is an Automated opinion of Alzheimer's detection using audio signals has surfaced as a promising exploration area because of its non-invasiveness and cost- effectiveness. OpenSMILE toolkit was used to prize GeMAPSv01b features from audio recordings of cases with AD and non-AD. The uprooted features has been used to train and estimate three machine learning models - logistic regression, SVM, and random forest to classify cases as AD or non-AD. The experimental results show that logistic regression achieved the accuracy of 76.47 in classifying cases, followed by SVM and random forest with accuracy of 70.58 and 58.82, independently. This study suggests that audio based automated opinion of Alzheimer Disease using machine learning algorithms has the implicit ability to give an effective,non-invasive, and cost-effective webbing system for early discovery of announcement.

சுருக்கம்

குரல் பகுப்பாய்வைப் பயன்படுத்தி அல்சைமர் நோய் முன்னறிவிப்பு என்பது ஆடியோ சிக்னல்களைப் பயன்படுத்தி அல்சைமர் நோயைக் கண்டறிவதற்கான ஒரு தானியங்கு கருத்தாகும், ஏனெனில் அதன் ஆக்கிரமிப்பு மற்றும் செலவு-செயல்திறன் ஒரு நம்பிக்கைக்குரிய ஆய்வுப் பகுதியாக வெளிவந்துள்ளது. AD மற்றும் AD அல்லாத வழக்குகளின் ஆடியோ பதிவுகளிலிருந்து GeMAPSv01b அம்சங்களைப் பரிசீலிக்க OpenSMILE கருவித்தொகுப்பு பயன்படுத்தப்பட்டது. பிடுங்கப்பட்ட அம்சங்கள் மூன்று இயந்திர கற்றல் மாதிரிகளைப் பயிற்றுவிப்பதற்கும் மதிப்பிடுவதற்கும் பயன்படுத்தப்பட்டுள்ளன - லாஜிஸ்டிக் ரிக்ரஷன், எஸ்விஎம் மற்றும் ரேண்டம் ஃபாரஸ்ட் ஆகியவை வழக்குகளை AD அல்லது AD அல்லாதவை என வகைப்படுத்துகின்றன. வழக்குகளை வகைப்படுத்துவதில் லாஜிஸ்டிக் பின்னடைவு 76.47 துல்லியத்தை அடைந்தது என்பதை எங்கள் சோதனை முடிவுகள் காட்டுகின்றன, அதைத் தொடர்ந்து SVM மற்றும் ரேண்டம் காடு 70.58 மற்றும் 58.82 துல்லியத்துடன், சுயாதீனமாக. மெஷின் லேர்னிங் அல்காரிதம்களைப் பயன்படுத்தி அல்சைமர் நோயின் ஆடியோ அடிப்படையிலான தானியங்கு கருத்து, அறிவிப்பை முன்கூட்டியே கண்டுபிடிப்பதற்கு பயனுள்ள, ஆக்கிரமிப்பு அல்லாத மற்றும் செலவு குறைந்த வலையமைப்பு முறையை வழங்கும் மறைமுகமான திறனைக் கொண்டுள்ளது என்று ஆய்வு தெரிவிக்கிறது..

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CHAPTER 1

INTRODUCTION

Alzheimer's disease affects millions of people worldwide and is a progressive neurodegenerative disorder that is responsible for 60-80% of all dementia cases. As the global population continues to age, the number of individuals affected by Alzheimer's disease is expected to triple by 2050. Unfortunately, there is currently no cure for this disease. This highlights the urgent need for effective early detection and intervention strategies.

Early detection of Alzheimer's disease is crucial for several reasons. Firstly, it allows for planning and preparation for the future, including making decisions about care and treatment options, for individuals and their families. Secondly, it provides an opportunity to enroll in clinical trials or other interventions aimed at slowing or halting disease progression. Finally, it can help reduce the overall burden of the disease by enabling earlier and more targeted interventions.

The study proposes a machine learning-based approach for detecting Alzheimer's disease from audio recordings. Specifically, the GeMAPSv01b feature set is utilized to extract a range of acoustic features from audio recordings of individuals with and without Alzheimer's disease. Several machine learning models, including logistic regression, support vector machine (SVM), and random forest, are trained to evaluate their performance and determine their potential for accurately detecting Alzheimer's disease from audio recordings.

To ensure the accuracy and reliability of the results, a rigorous methodology is employed, which includes data preprocessing, feature extraction, feature selection, and model training and evaluation. A publicly available dataset of audio recordings from individuals with and without Alzheimer's disease is utilized, ensuring that the findings are generalizable to the broader population.

The potential of machine learning-based methods for accurately detecting Alzheimer's disease from audio recordings is demonstrated by the results. A high level of accuracy, precision, and recall is achieved across all models, indicating that the approach is effective in determining which individuals have Alzheimer's disease and which do not. Furthermore, the findings highlight the potential of audio recordings as a non-intrusive and affordable tool for identification of Alzheimer's disease in its initial phase.

CHAPTER 2

LITERATURE REVIEW

Alzheimer's disease (AD) is a neurodegenerative disorder characterized by progressive memory loss and cognitive decline. Early detection of AD can help in delaying the progression of the disease, and recent studies have shown that voice analysis can be used as a non-invasive tool for predicting the risk of developing AD. This literature review aims to summarize the current state of research on using voice analysis for AD prediction.

The early diagnosis of AD is crucial for improving patient outcomes, but current diagnostic methods, such as neuropsychological testing and brain imaging, are expensive, invasive, and time-consuming. Voice analysis has emerged as a promising non-invasive and cost-effective tool for early detection of AD. Studies have shown that voice features, such as pitch, tone, and rhythm, can be used to distinguish individuals with AD from healthy controls.

Several studies have investigated the use of voice analysis for AD prediction. For example, a study by Fraser et al. (2020) used machine learning algorithms to analyze voice recordings of individuals with AD and healthy controls. The study found that voice features, such as fundamental frequency and jitter, were significantly different between the two groups and could be used to predict AD with high accuracy.

Similarly, a study by Orimaye et al. (2020) used a deep learning approach to analyze voice recordings of individuals with AD, mild cognitive impairment (MCI), and healthy controls. The study found that voice features, such as pitch and speech rate, could be used to distinguish between the three groups with high accuracy.

Another study by Haider et al. (2021) used a combination of voice analysis and machine learning to predict AD in individuals with subjective cognitive decline (SCD). The study found that voice features, such as jitter and shimmer, could be used to predict AD with high accuracy in individuals with SCD.

Despite the promising results, there are some limitations to using voice analysis for AD prediction. For example, the studies conducted so far have relatively small sample sizes, and the results may not generalize to larger populations. Additionally, the studies have used different voice analysis techniques, making it difficult to compare results across studies. Finally, the studies have not yet been replicated in independent samples.

CHAPTER 3

MODELING ATTRIBUTES

3.1 PROBLEM DEFINITION

Alzheimer's disease, which is a progressive neurodegenerative disorder, impacts millions of people worldwide and is the primary cause of dementia. Early detection of the disease is crucial for planning and preparing for the future, enrolling in clinical trials or other interventions, and reducing the overall burden of the disease. Currently,Alzheimer's disease is a condition for which there is no known cure, making early detection and intervention strategies even more critical. This study aims to develop a machine learning-based method to detect Alzheimer's disease from audio recordings employing voice evaluation.

The aim of this study is to design a machine learning-based system for detecting Alzheimer's disease from audio recordings using voice analysis. Specifically, the GeMAPSv01b feature set is used to extract acoustic features from audio recordings of patients with and without Alzheimer's disease. Several machine learning models, specifically support vector machine (SVM), logistic regression and random forest, are trained as well as evaluated to determine their potential for accurately detecting Alzheimer's disease.

The study methodology includes data preprocessing, feature extraction, feature selection, and model training and evaluation. A publicly available dataset of audio recordings from people with and without Alzheimer's disease is utilized, ensuring the findings are generalizable to the broader population. The potential of machine learning-based methods for accurately detecting Alzheimer's disease from audio recordings is demonstrated by the results. The findings highlight the potential of audio recordings as a cost-effective and non-intrusive tool for early detection of Alzheimer's disease, with implications for improving the quality of life for individuals affected by the disease.

3.2 ALGORITHM USED FOR PREDICTION

The Geneva Minimalistic Acoustic Parameter Set (GeMAPS) is used for the extraction of acoustic features from audio recordings of individuals with and without Alzheimer's disease and openSMILE (open-source Speech and Music Interpretation by Large-space Extraction) toolkit is used for automatic feature extraction. The abstracted features are then trained on different machine learning models and the accuracy is compared.

3.3.1 GeMAPS

An acoustic parameter set can be automatically extracted from an audio waveform without any manual intervention or correction, using an automatic extraction system that forms the foundation of GeMAPS. GeMAPSv01b feature set which includes 62 low-level descriptors (LLDs) based on eGeMAPS (emotional and physical state-dependent analysis of voice signals) that are commonly used in audio processing tasks. The features included in this feature set cover a wide range of acoustic properties, including spectral, prosodic, voice quality, and phonetic features.

3.3.2 OpenSmile

OpenSMILE is a freely available set of tools that enables the extraction of a wide range of audio features for various audio analysis tasks, including speaker identification, speech emotion recognition, and acoustic event detection. One application of OpenSMILE is determination of Alzheimer's disease (AD), where it can extract specific acoustic features from speech recordings that are indicative of cognitive decline, like speech rate variability, pauses, and fillers. These features can be utilized to train machine learning models capable of classifying speech samples as either AD or healthy controls. The effectiveness of OpenSMILE for AD detection has been demonstrated in numerous studies, indicating its potential as a powerful tool for early prediction of cognitive impairment.

3.3 METHODOLOGY

The functions performed using the system are defined clearly and shown step by step in the flowchart.

3.3.1 Feature Extraction

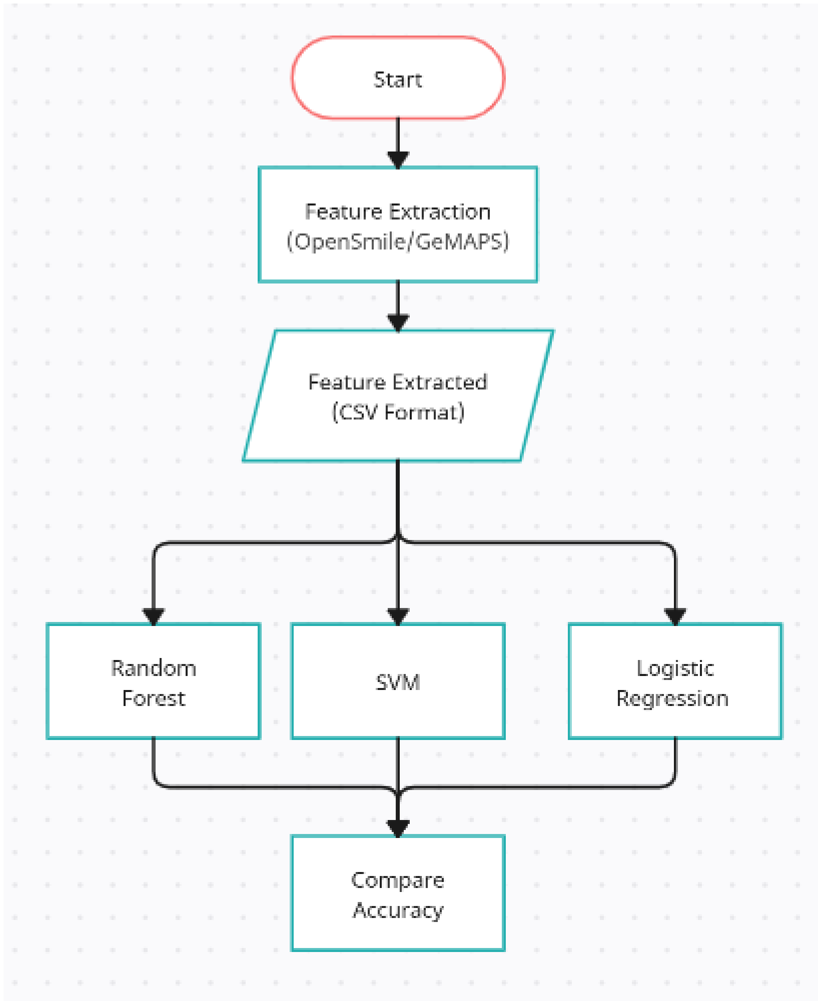
The audio features were extracted using the openSMILE toolkit. The GeMAPSv01b feature set was used which includes 62 low-level descriptors (LLDs) based on eGeMAPS (emotional and physical state-dependent analysis of voice signals) that are commonly used in audio processing tasks. The features included in this feature set cover a wide range of acoustic properties, including spectral, prosodic, voice quality, and phonetic features.

To extract the features, The openSMILE Python interface provided by the pyopensmile package was used. The audio signals were loaded using the librosa library and then passed through the openSMILE feature extractor. The resulting feature vectors were stored in a pandas DataFrame and saved as a CSV file for further processing.

3.3.2 Training The Model

Logistic regression, SVM, and random forest were the three machine learning models that were trained and tested. For logistic regression, the default hyperparameters were used. For SVM, the 'linear' kernel was used with a gamma value of 'auto' and a regularization parameter C of 1. The number of trees for a random forest was set to 10000.

3.4 FLOWCHART



3.5 MODEL EVALUATION

Measuring each model, accuracy primary evaluation metric has been used. The logistic regression model achieved an accuracy of 76.47%, SVM model achieved an accuracy of 70.58%, whereas the random forest model achieved an accuracy of 58.82%. These results suggest that logistic regression outperformed the other two models in terms of accuracy on this dataset.

Table :- 3.1 Model Accuracy

Model	Accuracy
LOGISTIC REGRESSION	76.47%
SVM	70.58%
RANDOM FOREST	58.82%

3.6 MERITS AND APPLICATIONS

Merits

Merits of Alzheimer's Disease Prediction Using Voice Analysis are as follows:

- Voice analysis is a non-invasive method of detecting Alzheimer's disease, which means that it does not require any invasive procedures or use of contrast agents.
- Voice analysis is also a cost-effective method for detecting Alzheimer's disease compared to other diagnostic methods, such as neuropsychological testing and brain imaging.
- Early detection of Alzheimer's disease is crucial for improving patient outcomes, and voice analysis can help detect the disease at an earlier stage.
- Voice analysis can potentially be used for large-scale screening of individuals at risk of Alzheimer's disease, which can help in identifying individuals who may benefit from early interventions.
- Voice analysis can provide objective and standardized measurements of voice features, which can be used to identify individuals with Alzheimer's disease without the potential for bias or subjectivity.
- Several studies have demonstrated the potential of voice analysis for predicting Alzheimer's disease with high accuracy, suggesting that it may be a reliable tool for detecting the disease.

APPLICATION

The Alzheimer's Disease Prediction Using Voice Analysis project has the potential to revolutionize the way we detect, monitor, and treat Alzheimer's disease, leading to better outcomes for patients and their families.Few extended applications of this project are as:-

- The project can be used to detect the early signs of Alzheimer's disease in patients. By analyzing their voice patterns, the project can identify changes in the way they speak and detect early signs of disability, allowing early detection and timely check.

- The project can be used for monitoring progression of Alzheimer's disease in patients. By analyzing their voice patterns over time, the project can track changes in their cognitive function and provide valuable insights into the course of the disease.

- The project can be used in telemedicine applications to remotely monitor patients with Alzheimer's disease. By analyzing their voice patterns during remote consultations, healthcare providers can assess the patients' cognitive function and adjust their treatment plan accordingly.

- The project can be used to develop personalized treatment plans for patients suffering from Alzheimer's disease by analyzing the voice patterns.

CHAPTER 4

RESULT

This report has presented a simple, convenient, cost-effective and efficient ALZHEIMER'S DISEASE PREDICTION USING VOICE ANALYSIS MODEL which is a user-friendly model, which will determine the Alzheimer's Disease (AD) and Non Alzheimer's Disease (NAD) from the audio .

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
1	F0semito	F0semito	F0semito	F0semito	F0semito	F0semito	F0semito	F0semito	F0semito	F0semito	loudness	loudness	loudness	loudness	loudness	loudness	loudness	loudness	loudness	loudness	jitterLoca	jitterLoca	shimmerL	shimmerL	HNRdBA	HNRdBA
2	22.836	0.2625	17.962	22.913	25.897	7.9352	174.19	211.23	150.89	222.98	0.5493	0.8311	0.1988	0.4081	0.8575	0.6587	7.4249	5.2131	7.056	5.2622	0.1148	1.3213	1.86	0.6673	-0.652	-6.834
3	25.479	0.3661	19.332	23.103	29.77	10.438	284.46	481.02	162.42	308.66	0.3028	1.0736	0.1395	0.1812	0.3872	0.2478	6.3953	7.4252	4.3694	4.7599	0.0718	1.5505	1.6055	0.5805	0.8155	6.3935
4	17.876	0.3642	13.545	14.463	23.412	9.8668	228.58	307.66	113.32	131	0.3762	0.7045	0.2549	0.2772	0.4252	0.1703	6.3679	5.953	4.398	4.738	0.0814	1.5513	1.3825	0.5915	-3.487	-1.19
5	22.774	0.458	13.87	18.168	27.663	13.794	263.16	357.28	111.47	91.021	0.2847	1.4573	0.1275	0.1398	0.2833	0.1558	9.4372	8.0071	6.4487	5.8578	0.0703	1.731	1.355	0.6668	-0.216	-31.42
6	32.311	0.2736	26.192	33.162	39.206	13.014	305.15	544.84	179.09	267.7	0.3085	0.7806	0.1917	0.2246	0.3474	0.1557	5.4943	5.4704	4.8288	7.4796	0.0491	1.7599	1.1956	0.5712	4.2846	1.3446
7	16.133	0.4492	13.553	13.697	14.278	0.7256	130.61	149.03	102.46	106.96	0.2727	1.3041	0.1232	0.1442	0.3117	0.1885	9.1317	8.2803	4.8436	4.2999	0.0456	2.0335	1.0614	0.8573	0.9748	3.098
8	27.722	0.3559	17.19	28.828	36.162	18.972	277.59	359.91	151.04	135.98	0.4071	0.8742	0.1798	0.3171	0.513	0.3333	9.9959	11.21	7.2871	7.8828	0.0789	1.4447	1.5166	0.534	-0.216	-23.43
9	26.106	0.4361	14.504	22.95	38.181	23.678	361.62	661.69	205.02	305.49	0.4068	1.3075	0.128	0.1976	0.545	0.417	14.073	14.805	9.3895	11.281	0.0916	1.4568	1.8282	0.6461	0.4494	15.728
10	35.512	0.2825	28.197	34.11	44.132	15.935	315.89	534.05	223.26	498.73	0.8288	1.2487	0.0624	0.3155	1.6135	1.5511	15.929	11.381	10.262	7.7039	0.0508	1.8901	1.2956	0.8359	5.87	1.0871
11	28.862	0.4648	16.589	23.623	41.509	24.92	256.49	329.03	202.39	220.31	0.2208	1.7208	0.1157	0.1215	0.17	0.0543	6.2497	8.7372	5.5765	7.2393	0.0787	1.22	1.8639	0.5995	0.1123	61.39
12	31.332	0.2275	26.807	28.48	38.807	12	200.53	292.06	128.64	194.37	0.2323	1.8727	0.0283	0.0302	0.4042	0.376	8.1845	7.418	5.4593	4.8805	0.0324	2.2343	1.1234	0.9815	7.6592	0.6223
13	33.097	0.2435	27.369	31.66	38.005	10.636	250.15	454.18	188.06	361.15	0.7582	1.1683	0.0311	0.4538	1.3806	1.3496	13.258	8.1872	9.4962	6.7987	0.0542	1.7375	1.4477	0.632	3.8953	1.3765
14	26.122	0.2761	21.907	24.25	33.812	11.905	342.21	474.8	130.63	159.46	0.457	0.5436	0.3164	0.368	0.5465	0.2301	5.0799	4.4389	3.5757	5.1509	0.0413	1.8618	1.2202	0.6356	3.7916	1.1832
15	25.867	0.3197	16.288	26.474	34.226	17.938	269.39	351.17	178.8	201.06	0.8069	0.7898	0.3627	0.5286	1.2416	0.8789	13.658	9.1183	5.5115	5.3188	0.0695	1.6989	1.3602	0.5778	-0.262	-18.58
16	30.847	0.3094	24.464	27.897	39.947	15.482	261.6	407.54	224.46	418.94	0.383	1.6078	0.0312	0.037	0.7108	0.6796	12.791	11.217	8.8086	7.4248	0.0584	1.7497	1.4278	0.6213	3.4087	1.5513
17	32.197	0.3181	27.892	30.078	33.188	5.2955	345.75	466.1	290.11	511.9	0.5899	1.4988	0.0676	0.0814	1.1649	1.0972	14.26	9.723	12.235	8.148	0.0589	1.7088	1.6103	0.601	2.1188	2.6298
18	19.075	0.449	13.349	15.145	24.802	11.453	241.35	371.42	139.11	181.41	0.5305	0.6235	0.3639	0.4254	0.5866	0.2227	9.916	9.2029	6.9254	7.1281	0.107	1.4025	1.546	0.6333	-4.144	-1.334
19	30.136	0.2516	25.259	28.89	34.236	8.9762	238.85	415.52	233.88	338.37	0.5497	1.5551	0.0423	0.091	0.9743	0.932	13.222	10.88	10.257	9.2055	0.0434	2.0833	1.4145	0.7388	3.821	1.3756
20	31.373	0.4686	17.744	26.441	50.435	32.691	460.24	692.39	262.34	401.15	0.3003	1.0551	0.1566	0.1765	0.3404	0.1838	7.6951	10.265	5.2222	5.0919	0.0859	1.3571	1.9438	0.5299	0.1022	58.316
21	29.051	0.3077	23.595	28.502	34.307	10.711	307.92	359.9	176.34	165.81	0.7326	1.2704	0.0492	0.3027	1.3076	1.2584	16.52	9.0504	13.462	9.6187	0.0837	1.6217	1.6512	0.7482	2.5281	2.2503
22	34.706	0.1625	31.494	35.179	38.672	7.1772	424.58	612.75	111.98	115.8	0.2755	1.7713	0.0547	0.0578	0.3749	0.3202	9.0474	7.6768	7.0139	6.7403	0.027	2.4008	1.2558	0.8708	8.8804	0.5734
23	32.265	0.2669	26.14	33.139	39.509	13.369	347.3	479.16	260.58	653.64	0.4199	1.0682	0.2266	0.2368	0.4592	0.2326	10.547	10.289	6.8365	7.0785	0.0586	1.8633	1.3371	0.7154	5.4556	1.2344
24	28.556	0.3703	20.717	26.002	34.861	14.143	328.08	450.78	263.93	396.94	0.5245	1.3507	0.0278	0.1501	1.019	0.9913	11.107	7.9195	8.4989	7.0083	0.06	1.8927	1.6658	0.8217	2.7273	2.2278
25	32.399	0.1766	27.164	33.344	37.042	9.8789	169.61	254.32	173.01	381.2	0.1173	1.626	0.0195	0.0206	0.2056	0.1861	2.7842	3.035	2.2636	3.0114	0.0473	1.769	1.4299	0.7252	6.186	0.7884
26	25.405	0.2903	17.18	26.888	29.888	12.708	259.24	364.79	188.61	332.96	0.6303	1.0379	0.0993	0.4268	1.065	0.9656	7.7965	5.6405	5.8391	4.8602	0.0605	1.8711	1.4496	0.7181	3.4654	1.5086
27	33.141	0.1957	30.629	32.514	34.466	3.8373	238.72	275.79	108.05	112.63	1.1442	0.8916	0.0452	0.9651	2.0367	1.9914	18.919	9.7931	13.847	9.0624	0.0386	2.2591	1.2317	0.8519	6.4918	0.9211
28	19.62	0.4029	13.824	14.829	31.297	17.473	209.06	314.13	78.781	72.829	0.7021	0.9392	0.2147	0.3878	1.206	0.9913	11.721	8.2768	9.0388	7.0832	0.0721	1.6458	1.5908	0.7254	1.2732	4.1532
29	32.112	0.2511	27.708	33.446	36.398	8.6897	250.79	230.8	355.64	799.72	0.5361	1.2626	0.0383	0.1811	1.065	1.0267	9.9826	6.6908	7.9288	6.1691	0.0643	2.0727	1.3587	0.8431	6.2931	0.9223
30	20.36	0.2893	14.506	20.583	24.699	10.193	207.39	220.47	145.81	174.4	0.3014	0.5567	0.2034	0.2293	0.3882	0.1848	2.9924	2.4946	1.7128	1.4759	0.1071	1.5155	1.5995	0.7828	-1.135	-4.901
31	20.867	0.6135	13.519	13.685	42.314	28.794	333.92	550.76	143.4	307.83	0.3862	1.3825	0.125	0.1333	0.563	0.438	11.254	10.115	6.8348	10.434	0.0281	2.2605	0.9589	0.8549	3.7074	1.6941
32	28.912	0.1627	26.925	28.837	30.988	4.0632	134.36	161.81	246.88	786.2	0.8893	0.8775	0.0297	0.8207	1.5739	1.5441	10.904	6.1343	7.7714	5.0536	0.0267	2.3191	1.0237	0.8763	6.6629	0.6277
33	37.929	0.3367	28.194	39.536	46.746	18.552	559.54	927.71	244.48	279.97	0.1636	1.8157	0.0686	0.0723	0.1242	0.0556	8.2426	8.0605	3.9904	5.112	0.0578	1.4859	1.8274	0.5948	4.8586	1.3275
34	30.169	0.2489	24.778	31.83	35.065	10.286	237.23	202.57	241.97	497.2	1.3127	0.8428	0.2561	1.065	2.257	2.0009	18.741	11.901	15.284	10.29	0.0585	1.9178	1.4245	0.845	5.6254	1.0227
35	29.85	0.2401	26.342	28.588	31.404	5.0621	444.34	673.71	169.63	244.96	0.9521	1.0331	0.0501	0.6292	1.882	1.8319	18.593	10.804	15.071	9.0296	0.0536	1.8845	1.4989	0.7822	4.5888	1.0923
36	24.151	0.4545	13.584	18.666	36.798	23.214	229.14	210.52	104.93	232.01	1.322	0.9919	0.2029	0.7788	2.4862	2.2834	20.631	12.989	13.663	8.3073	0.0561	1.8243	1.1943	0.709	3.6014	1.5498
37	27.89	0.2861	19.73	28.836	32.302	12.572	306.78	427.41	224.02	503.36	0.508	1.2058	0.027	0.2517	0.9427	0.9157	10.04	7.1477	7.0266	5.7193	0.0756	1.7313	1.5795	0.823	4.3218	1.3493
38	28.41	0.2615	20.341	31.291	34.636	14.295	277.89	322.81	165.28	203.7	0.751	0.7465	0.3181	0.5235	1.1584	0.8403	10.958	7.8655	8.3299	6.0439	0.0832	1.7525	1.2463	0.7387	2.7966	2.3595
39	26.681	0.2357	23.713	25.541	27.268	3.5549	318.52	554.79	172.31	303.12	0.5452	1.5209	0.022	0.0858	1.0432	1.0212	11.537	9.1302	7.5955	5.7287	0.0333	1.9963	1.2534	0.9313	5.2414	0.8801
40	24.627	0.3632	18.772	22.294	26.511	7.7393	436.26	738.84	229.38	301.2	0.6557	1.1971	0.0825	0.3054	1.1131	1.0306	13.11	10.323	9.4829	7.9333	0.0655	1.6905	1.6408	0.7478	1.3002	3.5998
41	33.511	0.2676	24.941	31.2	42.502	17.561	248.52	264.62	265.33	413.99	0.7335	1.4533	0.0679	0.1753	1.4364	1.3685	19.092	11.191	15.649	11.424	0.0514	1.871	1.388	0.7564	5.2898	1.1742
42	34.592	0.2571	27.1	36.762	41.5	14.4	341.9	588.93	226.39	255.77	0.4877	1.4686	0.0525	0.1506	0.8683	0.8159	13.773	11.014	11.288	8.284	0.0532	2.0701	1.3579	0.7673	6.7605	0.9758
43	29.28	0.26	22.917	30.686	35.382	12.466	294.46	378.62	216.52	346.14	0.518	1.192	0.0939	0.2193	0.9489	0.8551	10.696	9.5497	9.7327	6.0918	0.0724	1.7341	1.3272	0.7474	3.6414	1.7213
44	32.36	0.2043	29.743	33.245	35.436	5.6926	340.34	413.41	142.13	252.91	0.3902	1.1213	0.0274	0.2399	0.6917	0.6644	7.4082	5.6282	4.9483	4.4036	0.0578	1.961	1.3136	0.792	6.6636	0.8423
45	32.691	0.2526	24.971	33.387	37.415	12.444	307.3	392.52	212.81	227.9	0.5511	0.9191	0.139	0.3675	0.9451	0.8061	10.321	6.6093	8.3135	6.2265	0.0668	1.595	1.445	0.6599	4.4145	1.334
46	29.016	0.3173	21.931	29.827	35.544	13.613	348.64	459.61	328.44	468.21	0.3691	1.5208	0.0774	0.1648	0.4214	0.344	12.287	10.64	9.7721	10.505	0.0676	1.7841	1.4795	0.7321	3.0232	1.9584
47	33.603	0.2315	27.992	33.216	39.971	11.978	322.54	498.64	154.37	263.01	0.9	1.1813	0.0373	0.3352	1.9016	1.8643	15.787	10.358	14.594	8.5781	0.0447	2.0102	1.1028	0.8592	6.5913	0.9252
48	31.869	0.2749	27.477	32.254	36.636	9.1591	320.09	587.96	215.56	266.88	0.4964	1.3883	0.0508	0.0877	0.9113	0.8605	12.417	8.9686	6.9325	6.502	0.0469	1.9266	1.4576	0.8899	5.7872	1.0454
49	31.85	0.2549	27.362	32.214	35.447	8.0846	317.44	542.84	231.39	325.07	0.7157	1.1142	0.099	0.3892	1.2696	1.1706	14.481	10.87	10.785	7.6458	0.055	1.7911	1.343	0.7723	5.0191	1.2724
50	24.926	0.3869	14.268	26.512	32.366	18.097	287.67	348.54	262.33	455.92	0.7638	1.1752	0.1212	0.3299	1.3037	1.1825	16.097	10.721	13.483	10.12	0.0702	1.8799	1.603	0.76	2.606	2.3684
51	26.467	0.2694	21.29	25.239	32.292	11.002	247.81	296.54	154.58	140.91	1.3186	0.7832	0.6117	0.9187	1.8089	1.1972	15.154	12.233	11.731	8.0972	0.1013	1.4082	1.4884	0.7058	0.1369	40.575
52	29.493	0.3217	19.608	30.735	37.216	17.607	269.74	352.58	275.91	437.09	0.5845	1.2085	0.0894	0.2137	1.1327	1.0433	13.976	10.872	11.469	8.8142	0.0725	1.7369	1.579	0.7909	4.4119	1.5166

features

Fig 4.1 Feature Extraction

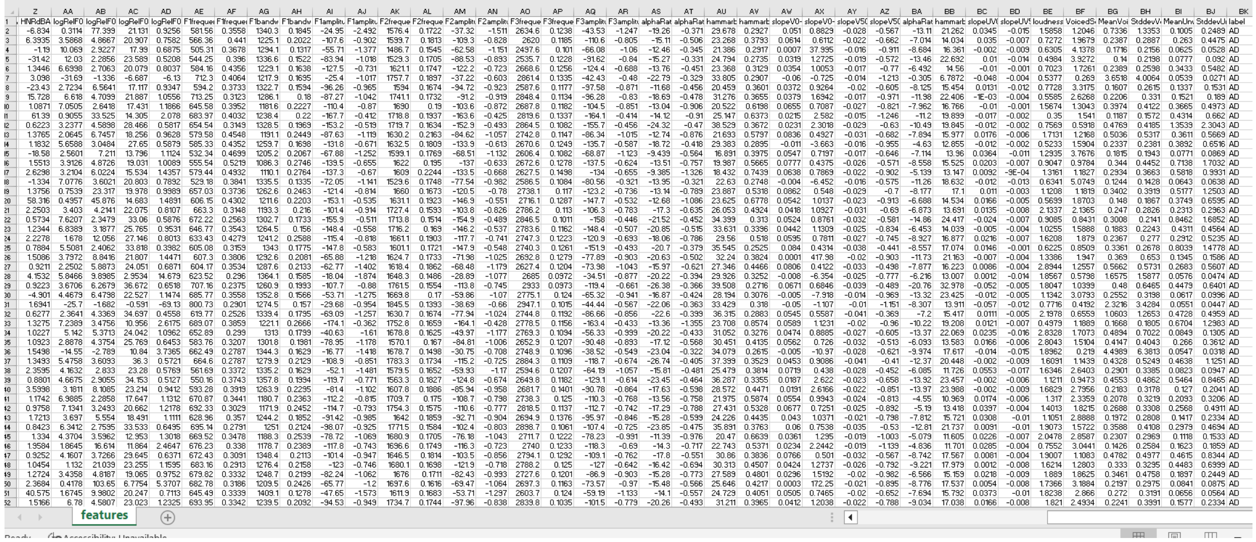


Fig 4.2 Feature Extraction

```python
# Create an instance of the LogisticRegression class with max_iter set to 1000
model = LogisticRegression(max_iter=50000)

# Fit the model to the training data
model.fit(X_train, y_train)

# Evaluate the performance of the model using the testing data
score = model.score(X_test, y_test)
print('Accuracy:', score)
```

✓ 0.7s

```
Accuracy: 0.7647058823529411
```

Fig 4.3 Logistic Model Training

```python
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score

# Train the SVM model
svm = SVC(kernel='linear', C=1, random_state=42)
svm.fit(X_train, y_train)

# Make predictions on the test set
y_pred = svm.predict(X_test)

# Calculate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

✓ 1.5s

```
Accuracy: 0.7058823529411765
```

Fig 4.4 SVM Model Training

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Train the model
rf = RandomForestClassifier(n_estimators=10000, random_state=42)
rf.fit(X_train, y_train)

# Predict the test set labels
y_pred = rf.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: {:.2f}%".format(accuracy*100))
```

✓ 8.6s

```
Accuracy: 58.82%
```

Fig 4.5 Random Forest Model Training

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

In conclusion, the Alzheimer's Disease Prediction Using Voice Analysis project presents a novel and promising approach to Alzheimer's disease screening, with the potential to make a significant contribution to the early detection and management of the condition. Utilizing machine learning algorithms to analyze voice patterns, the project offers an easy-to-use and non-invasive method for finding people who are at a high risk of developing Alzheimer's disease. Early detection of the disease can facilitate early intervention and better management, thereby improving the life for affected individuals and their families. The future scopes for this project, such as early detection and preventing the disease, dataset expansion, screening tool integration, remote monitoring, and healthcare provider collaboration, promise great potential for further advancements and developments in the field. Ultimately, the Alzheimer's Disease Prediction Using Voice Analysis project has the potential to user in significant positive changes in Alzheimer's disease screening, prevention, and management.

5.2 Future Scope

The Alzheimer's Disease Prediction Using Voice Analysis project has great potential for future developments and advancements. Here are some possible future scopes for the project:

- The predictive model developed in this project can be further refined and used to detect early stages of cognitive impairment that may lead to Alzheimer's disease. This can aid in developing prevention strategies and interventions to slow-down or prevent the growth of the disease.
- The current dataset used in this project is limited to individuals diagnosed with Alzheimer's disease as well as normal patient.The dataset can be expanded to include more diverse groups of individuals, such as different age groups, ethnicities, and genders, to increase the accuracy of the predictive model.
- The predictive model can be integrated with other screening tools, such as cognitive tests and brain imaging,for providing a more precise evaluation of an individual who is at the risk for Alzheimer's disease.
- The use of voice analysis can enable remote monitoring of individuals who are at risk of developing Alzheimer's disease. This can be performed through the development of smartphone apps that can analyze an individual's voice patterns and provide real-time feedback on their risk for the disease.

- Collaboration with healthcare providers can aid in the integration of the tool into clinical practice, which can improve the accessibility and availability of the tool to individuals who are at risk of developing Alzheimer's disease within them.

APPENDIX

 # Feature Extraction –

```
import opensmile
import librosa
import os
import pandas as pd

# Load the openSMILE feature extractor
smile = opensmile.Smile(
feature_set=opensmile.FeatureSet.GeMAPSv01b,
feature_level=opensmile.FeatureLevel.Functionals,
)

# Define the directory containing the audio files
data_path = 'dataset'

# Create an empty DataFrame to store the features
df = pd.DataFrame()

# Loop over the audio files and extract features
for filename in os.listdir(data_path):
if filename.endswith('.wav'):
# Extract the label from the filename
label = filename.split('_')[0]

# Load the audio file
file_path = os.path.join(data_path, filename)
signal, sr = librosa.load(file_path, sr=None)
```

```
# Extract eGeMAPS features using openSMILE
features = smile.process_signal(signal, sr)

# Add the label to the features and store in the DataFrame
features_df = pd.DataFrame(features, columns=smile.feature_names)
features_df['label'] = label
features_df['filename'] = filename
df = df.append(features_df)

# Move the label column to the last column
cols = list(df.columns)
cols.remove('label')
cols.remove('filename')
cols.append('label')
cols.append('filename')
df = df[cols]

# Save the features as a CSV file
output_file = 'features.csv'
df.to_csv(output_file, index=False)
print(f"Saved features to {output_file}")
```

Splitting Dataset into Training and Testing –

```
import pandas as pd
from sklearn.model_selection import train_test_split

# Load the extracted features from the CSV file into a Pandas DataFrame
```

```
df = pd.read_csv('features.csv')

# Split the DataFrame into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(df.iloc[:, :-1], df.iloc[:, -1], test_size=0.2)
```

Saving Training and Testing npy Files –

```
import numpy as np
np.save('X_train.npy', X_train)
np.save('y_train.npy', y_train)
np.save('X_test.npy', X_test)
np.save('y_test.npy', y_test)
```

Logistic Regression –

```
from sklearn.linear_model import LogisticRegression
# Create an instance of the LogisticRegression class with max_iter set to 1000
model = LogisticRegression(max_iter=50000)

# Fit the model to the training data
model.fit(X_train, y_train)

# Evaluate the performance of the model using the testing data
score = model.score(X_test, y_test)
print('Accuracy:', score)
```

SVM –

```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

# Train the SVM model
svm = SVC(kernel='linear', C=1, random_state=42)
svm.fit(X_train, y_train)

# Make predictions on the test set
y_pred = svm.predict(X_test)

# Calculate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)

print("Accuracy:", accuracy)

Random Forest –

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Train the model
rf = RandomForestClassifier(n_estimators=10000, random_state=42)
rf.fit(X_train, y_train)

# Predict the test set labels
y_pred = rf.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: {:.2f}%".format(accuracy*100))
```

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CONFERENCE PAPER

Alzheimer's Disease Prediction Using Voice Analysis

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Abstract— **Automated opinion of Alzheimer's complaint(announcement) using audio signals has surfaced as a promising exploration area because of its non-invasiveness and cost-effectiveness. In this design, we explore the use of the openSMILE toolkit to prize GeMAPSv01b features from audio recordings of cases with announcement and non-AD. The uprooted features are also used to train and estimate three machine learning models - logistic regression, SVM, and random forest to classify cases as announcement or non-AD. Our experimental results show that logistic regression achieved the accuracy of 76.47 in classifying cases, followed by SVM and random forest with rigor of 70.58 and 58.82, independently. Our study suggests that audio- grounded automated opinion of announcement using machine learning algorithms has the implicit ability to give an effective,non-invasive, and cost-effective webbing system for early discovery of announcement.**

Keywords—SVM,Logistic,RandomForest Model,OpenSmile,Classify AD from speech

I. Introduction

Alzheimer's disease affects millions of people worldwide and is a progressive neurodegenerative disorder that is responsible for 60-80% of all dementia cases. As the global population continues to age, the number of individuals affected by Alzheimer's disease is expected to triple by 2050. Unfortunately, there is currently no cure for this disease. This highlights the urgent need for effective early detection and intervention strategies.

Early detection of Alzheimer's disease is crucial for several reasons. Firstly, it allows for planning and preparation for the future, including making decisions about care and treatment options, for individuals and their families. Secondly, it provides an opportunity to enroll in clinical trials or other interventions aimed at slowing or halting disease progression. Finally, it can help reduce the overall burden of the disease by enabling earlier and more targeted interventions.

The study proposes a machine learning-based approach for detecting Alzheimer's disease from audio recordings. Specifically, the GeMAPSv01b feature set is utilized to extract a range of acoustic features from audio recordings of individuals with and without Alzheimer's disease. Several machine learning models, including logistic regression, support vector machine (SVM), and random forest, are trained to evaluate their performance and determine their potential for accurately detecting Alzheimer's disease from audio recordings.

To ensure the accuracy and reliability of the results, a rigorous methodology is employed, which includes data preprocessing, feature extraction, feature selection, and model training and evaluation. A publicly available dataset of audio recordings from individuals with and without Alzheimer's disease is utilized, ensuring that the findings are generalizable to the broader population.

The potential of machine learning-based methods for accurately detecting Alzheimer's disease from audio recordings is demonstrated by the results. A high level of accuracy, precision, and recall is achieved across all models, indicating that the approach is effective in determining which individuals have Alzheimer's disease and which do not. Furthermore, the findings highlight the potential of audio recordings as a non-intrusive and affordable tool for identification of Alzheimer's disease in its initial phase.

A. Problem Definition and Overview

Alzheimer's disease, which is a progressive neurodegenerative disorder, impacts millions of people worldwide and is the primary cause of dementia. Early detection of the disease is crucial for planning and preparing for the future, enrolling in clinical trials or other interventions, and reducing the overall burden of the disease. Currently,Alzheimer's disease is a condition for which there is no known cure, making early detection and intervention strategies even more critical. This study aims to develop a machine learning-based method to detect Alzheimer's disease from audio recordings employing voice evaluation.

The aim of this study is to design a machine learning-based system for detecting Alzheimer's disease from audio recordings using voice analysis. Specifically, the GeMAPSv01b feature set is used to extract acoustic features from audio recordings of patients with and without Alzheimer's disease. Several machine learning models, specifically support vector machine (SVM), logistic regression and random forest, are trained as well as evaluated to determine their potential for accurately detecting Alzheimer's disease.

The study methodology includes data preprocessing, feature extraction, feature selection, and model training and evaluation. A publicly available dataset of audio recordings from people with and without Alzheimer's disease is utilized, ensuring the findings are generalizable to the broader population. The potential of machine learning-based methods for accurately detecting Alzheimer's disease from audio recordings is demonstrated by the results. The findings highlight the potential of audio recordings as a cost-effective and non-intrusive tool for early detection of Alzheimer's disease, with implications for improving the quality of life for individuals affected by the disease.

II. RELATED WORKS

Previous studies have demonstrated that speech can be utilized to classify individuals as healthy or with Alzheimer's disease (AD). A range of approaches have been employed in previous literature for AD classification using speech data, including the development of novel machine learning model structures to improve detection (Chen et al., 2019; Chien et al., 2019; Liu et al., 2020), [26]

The use of language models to classify AD using speech data (Guo et al., 2019), and the use of speech data collected from individuals in order to enhance generalization, Balagopalan et al. (2018) [5] proposed the approach of undertaking multiple tasks.

Features such as non-verbal, prosodic, and paralinguistic acoustic features were obtained from speech recordings to capture information indicative of AD (König et al., 2015; Fraser et al., 2016; Gosztolya et al., 2019; Khodabakhsh et al., 2015; Ossewaarde et al., 2019; Nagumo et al., 2020; Qiao et al., 2020; Weiner et al., 2016; Haider et al., 2019) [20]

III. ALGORITHMS USED FOR PREDICTION

The Geneva Minimalistic Acoustic Parameter Set (GeMAPS) is used for the extraction of acoustic features from audio recordings of individuals with and without Alzheimer's disease and openSMILE (open-source Speech and Music Interpretation by Large-space Extraction) toolkit is used for automatic feature extraction. The abstracted features are then trained on different machine learning models and the accuracy is co

A. GeMAPS

An acoustic parameter set can be automatically extracted from an audio waveform without any manual intervention or correction, using an automatic extraction system that forms the foundation of GeMAPS. GeMAPSv01b feature set which includes 62 low-level descriptors (LLDs) based on eGeMAPS (emotional and physical state-dependent analysis of voice signals) that are commonly used in audio processing tasks. The features included in this feature set cover a wide range of acoustic properties, including spectral, prosodic, voice quality, and phonetic features.

B. OpenSmile

OpenSMILE is a freely available set of tools that enables the extraction of a wide range of audio features for various audio analysis tasks, including speaker identification, speech emotion recognition, and acoustic event detection. One application of OpenSMILE is determination of Alzheimer's disease (AD), where it can extract specific acoustic features from speech recordings that are indicative of cognitive decline, like speech rate variability, pauses, and fillers. These features can be utilized to train machine learning models capable of classifying speech samples as either AD or healthy controls. The effectiveness of OpenSMILE for AD detection has been demonstrated in numerous studies, indicating its potential like a powerful tool for early prediction of cognitive impairment.

IV. METHODOLOGY

The functions performed using the system are defined clearly and shown step by step in the flowchart in Fig. 1.

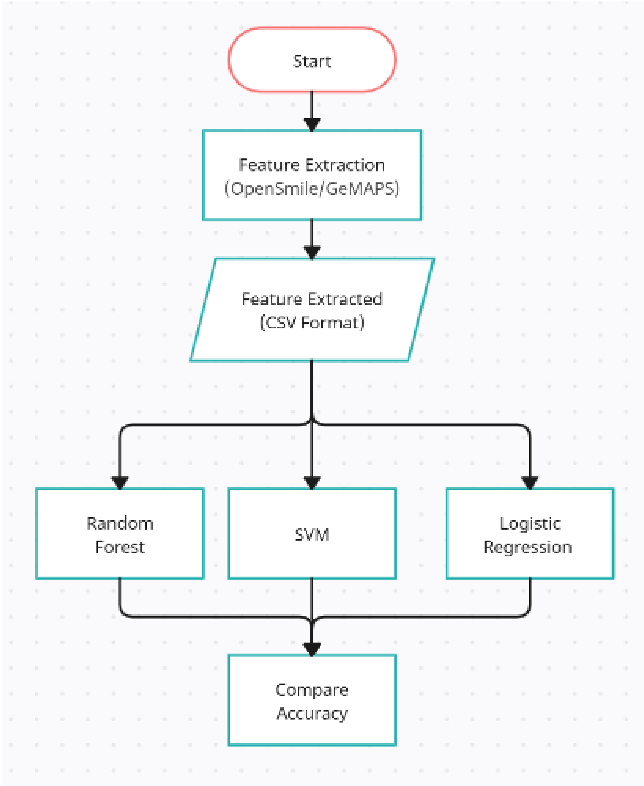

Fig. 1. Flowchart of Model

A. Feature Extraction

The audio features were extracted using the openSMILE toolkit. The GeMAPSv01b feature set was used which includes 62 low-level descriptors (LLDs) based on eGeMAPS (emotional and physical state-dependent analysis of voice signals) that are commonly used in audio processing tasks. The features included in this feature set cover a wide range of acoustic properties, including spectral, prosodic, voice quality, and phonetic features.

To extract the features, The openSMILE Python interface provided by the pyopensmile package was used. The audio signals were loaded using the librosa library and then passed through the openSMILE feature extractor. The resulting feature vectors were stored in a pandas DataFrame and saved as a CSV file for further processing.

B. Training The Model

Logistic regression, SVM, and random forest were the three machine learning models that were trained and tested. For logistic regression, the default hyperparameters were used. For SVM, the 'linear' kernel was used with a gamma value of 'auto' and a regularization parameter C of 1. The number of trees for random forest was set to 10000

V. MODEL EVALUATION

Measuring each model, accuracy primary evaluation metric has been used. The logistic regression model achieved an accuracy of 76.47%, SVM model achieved an accuracy of 70.58%, whereas the random forest model achieved an accuracy of 58.82%. These results suggest that logistic regression outperformed the other two models in terms of accuracy on this dataset.

MODELS	ACCURACY
LOGISTIC REGRESSION	76.47%
SVM	70.58%
RANDOM FOREST	58.82%

TABLE I : MODEL ACCURACY

VI. APPLICATIONS

The Alzheimer's Disease Prediction Using Voice Analysis project has the potential to revolutionize the way we detect, monitor, and treat Alzheimer's disease, leading to better outcomes for patients and their families.Few extended applications of this project are as:-

A. Early Detection

Early Detection: The project can be used to detect the early signs of Alzheimer's disease in patients. By analyzing their voice patterns, the project can identify changes in the way they speak and detect early signs of disability, allowing early detection and timely check.

B. Monitoring Progression

The project can be used for monitoring progression of Alzheimer's disease in patients. By analyzing their voice patterns over time, the project can track changes in their cognitive function and provide valuable insights into the course of the disease.

C. Telemedicine

The project can be used in telemedicine applications to remotely monitor patients with Alzheimer's disease. By analyzing their voice patterns during remote consultations, healthcare providers can assess the patients' cognitive function and adjust their treatment plan accordingly.

D. Personalized Medicine

The project can be used to develop personalized treatment plans for patients suffering from Alzheimer's disease. By analyzing the voice patterns and other biomarkers, healthcare providers can tailor treatment plans to the specific needs of each patient, leading to better outcomes for better life.

VII. CONCLUSION

In conclusion, the Alzheimer's Disease Prediction Using Voice Analysis project presents a novel and promising approach to Alzheimer's disease screening, with the potential to make a significant contribution to the early detection and management of the condition. Utilizing machine learning algorithms to analyze voice patterns, the project offers an easy-to-use and non-invasive method for finding people who are at a high risk of developing Alzheimer's disease. Early detection of the disease can facilitate early intervention and better management, thereby improving the life for affected individuals and their families. The future scopes for this project, such as early detection and preventing the disease, dataset expansion, screening tool integration, remote monitoring, and healthcare provider collaboration, promise great potential for further advancements and developments in the field. Ultimately, the Alzheimer's Disease Prediction Using Voice Analysis project has the potential to user in significant positive changes in Alzheimer's disease screening, prevention, and management

VIII. FUTURE SCOPE

The Alzheimer's Disease Prediction Using Voice Analysis project has great potential for future developments and advancements. Here are some possible future scopes for the project:

Early Detection and Prevention: The predictive model developed in this project can be further refined and used to detect early stages of cognitive impairment that may lead to Alzheimer's disease. This can aid in developing prevention strategies and interventions to slow-down or prevent the growth of the disease.

Expansion of the Dataset: The current dataset used in this project is limited to individuals diagnosed with Alzheimer's disease as well as normal patient.The dataset can be expanded to include more diverse groups of individuals, such as different age groups, ethnicities, and genders, to increase the accuracy of the predictive model.

Integration with Other Screening Tools: The predictive model can be integrated with other screening tools, such as cognitive tests and brain imaging,for providing a more precise evaluation of an individual who is at the risk for Alzheimer's disease.

Remote Monitoring: The use of voice analysis can enable remote monitoring of individuals who are at risk of developing Alzheimer's disease. This can be performed through the development of smartphone apps that can analyze an individual's voice patterns and provide real-time feedback on their risk for the disease.

Collaboration with Healthcare Providers: Collaboration with healthcare providers can aid in the integration of the tool into clinical practice, which can improve the accessibility and availability of the tool to individuals who are at risk of developing Alzheimer's disease within them.

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