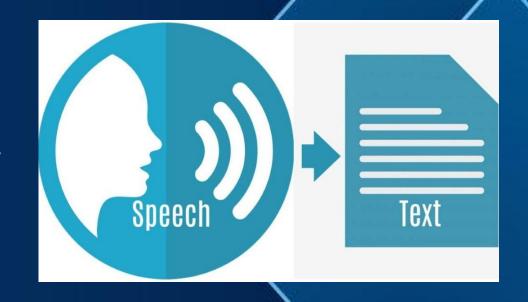


Group Members:

- 1. Ramiza Rahman Parsha (2122370642)
- 2. Tasnia Kibria (2013553642)

Introduction

- Goal: Build a model to recognize spoken commands.
- Dataset: Google Speech
 Commands v0.02.
- Focus: Comparing performance of KNN, Random Forest, and SVM models.



Dataset

- Source: TensorFlow Speech Commands dataset.
- Classes: 10 target words (e.g., Yes, No, Up, Down, Left, Right, On, Off, Stop, Go).
- Dataset Size: 38,546 samples initially,
 balanced to 37,230 samples
- File Format: WAV audio files

Data Preprocessing

Audio Features Extracted:

- MFCC (Mel-frequency Cepstral Coefficients)
- Delta MFCC (first derivative)
- Delta-delta MFCC (second derivative)

Normalization: StandardScaler to normalize features

Dimensionality Reduction: PCA to retain 95% variance

Model

Models Tested:

- K-Nearest Neighbors (KNN): Regularized with k=10
- Random Forest: Regularized with max depth=10, min samples=2
- SVM (Support Vector Machine): Regularized with Gaussian (RBF) kernel

Evaluation Metric: Accuracy, Precision, Recall, F1-Score, Confusion Matrix

Model Used and Effectiveness

Regularized K-Nearest Neighbors (KNN)

Why Used:

- KNN is a simple and intuitive algorithm for classification tasks. It is particularly useful for problems where the
 decision boundaries are non-linear. It performs well with smaller datasets and is easy to understand and
 implement.
- The model classifies each sample by looking at the "k" nearest data points in the feature space and predicting the most common label among these neighbors.

Effectiveness:

- Train Accuracy: 64.99%
- Test Accuracy: 51.02%
- The train accuracy is moderate, and the test accuracy is relatively low, indicating that KNN may not be generalizing well to unseen data. The low test accuracy suggests that it might be struggling with complex relationships between features and labels, as it has difficulty dealing with high-dimensional data (especially after PCA transformation).

Model Used and Effectiveness

Regularized Random Forest

Why Used:

- Random Forest is an ensemble learning method that builds multiple decision trees and combines their outputs for a final prediction. It's well-suited for handling non-linear relationships, imbalanced data, and feature interactions.
- The use of regularization parameters like limiting tree depth and increasing min_samples_split and min_samples_leaf helps in reducing overfitting, making the model more generalized.

Effectiveness:

- Train Accuracy: 78.68%
- Test Accuracy: 47.48%
- The model exhibits a higher training accuracy compared to the other models, which shows it fits well to the training data. However, the test accuracy is relatively low, indicating that Random Forest might still be overfitting, despite regularization. This means that the model is learning details specific to the training set rather than capturing general patterns in the data, which results in poor performance on new, unseen data.

Model Used and Effectiveness

Regularized SVM with Gaussian (RBF) Kernel

Why Used:

- Support Vector Machines (SVMs) with a Gaussian (RBF) kernel are often used for non-linear classification problems, as the RBF kernel can handle complex decision boundaries effectively.
- The use of regularization (C=0.5) helps in preventing overfitting by controlling the trade-off between achieving a high accuracy on training data and keeping the model's complexity manageable.
- The RBF kernel makes it possible to classify data that is not linearly separable by mapping it into a higher-dimensional space.

Effectiveness:

- Train Accuracy: 72.11%
- Test Accuracy: 62.13%
- SVM shows a moderate train accuracy and the highest test accuracy among the three models. This indicates that it is better at generalizing to unseen data compared to KNN and Random Forest. The regularization helps in balancing the model's ability to learn from the training data without overfitting, resulting in a relatively better performance on the test set.

Training and Testing

- Training/Testing Split: 80/20 (29,784 train, 7,446 test)
- Feature Scaling: StandardScaler applied to training and test data
- PCA Applied: Reduced feature space to 45 dimensions
- Model Evaluation: Accuracy scores and confusion matrices

Results

K-Nearest Neighbors (KNN):

- Train Accuracy: 64.99%
- **Test Accuracy:** 51.02%
- Key Observations:
 - High recall for words like "yes"
 - Lower accuracy for more difficult words like "down" and "off"
- Confusion Matrix: Visualized performance for test/train data

Regularized K-Nearest Neighbors Confusion Matrix (Test Data)												
down	416	82	27	91	8	21	45	17	29	8		- 500
ob -	86	391	17	133	15	21	29	24	23	5		
left -	114	59	320	71	8	9	75	26	31	32		- 400
인 -	102	154	23	379	12	24	22	4	18	7		
Actual off	26	46	15	34	405	86	16	38	76	3		- 300
Acti on	101	69	17	80	114		15	13	50	0		
right	79	43	49	70	8	10	425	17	11	33		- 200
stop	68	72	31	38	59	25	38	349	52	13		
g -	79	72	44	63	89	40	18	35	297	7		- 100
yes	48	21	29	40	7	7	54	4	3	532		
	down	go	left	no	off Pred	on icted	right	stop	up	yes		- 0

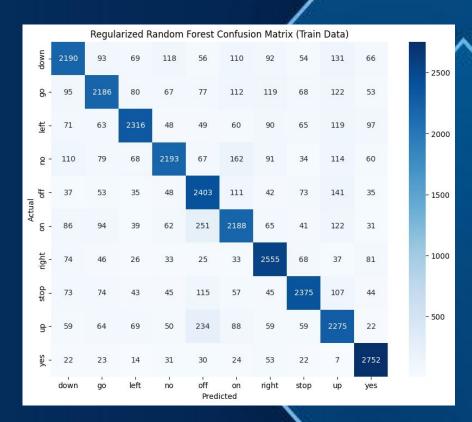
wop	2122	170	66	287	24	61	115	41	56	37			
g -	245	2062	53	360	29	51	65	30	70	14			- 2000
- E	307	225	1750	180	37	17	193	70	68	131			
요 -	326	460	84	1889	20	54	59	20	43	23			- 1500
JJo	117	159	52	116	1981	232	25	104	184	8			
등 -	309	238	62	257	290	1586	43	42	143	9			- 1000
right	276	135	159	175	13	20	2069	27	26	78			
stop -	200	221	107	142	143	89	108	1823	115	30			- 500
육 -	200	211	109	172	248	160	50	138	1684	7			
- yes	100	55	80	127	15	18	177	12	3	2391			
down go left no off on right stop up yes Predicted													

Results

Random Forest:

- Train Accuracy: 78.68%
- Test Accuracy: 47.48%
- Key Observations:
 - High accuracy on training data, lower on testing data
 - Misclassification between similar sounding commands
- Confusion Matrix: Visualized performance for test/train data

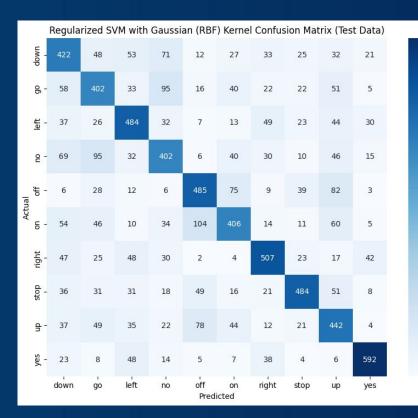
Regularized Random Forest Confusion Matrix (Test Data)												
down	- 250	45	66	82	25	53	96	35	46	46		
ob -	- 51	256	43	97	40	79	57	34	61	26		- 500
left -	- 42	33	263	51	30	34	92	56	58	86		
ou -	- 57	93	29	301	26	74	58	15	47	45		- 400
Actual	- 14	25	16	12	429	90	17	48	84	10		- 300
Acti on	- 53	46	25	43	128	334	24	19	56	16		
right 	- 45	28	58	33	11	12	413	32	15	98		- 200
stop	- 41	37	28	18	67	31	32	394	54	43		
슠-	- 46	44	39	32	113	65	38	48	308	11		- 100
yes -	- 11	4	24	17	10	13	54	16	9	587		
	down	go	left	no	off Pred	on icted	right	stop	up	yes		

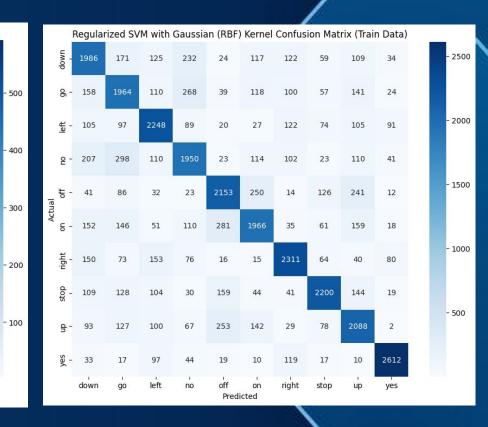


Results

Support Vector Machine (SVM):

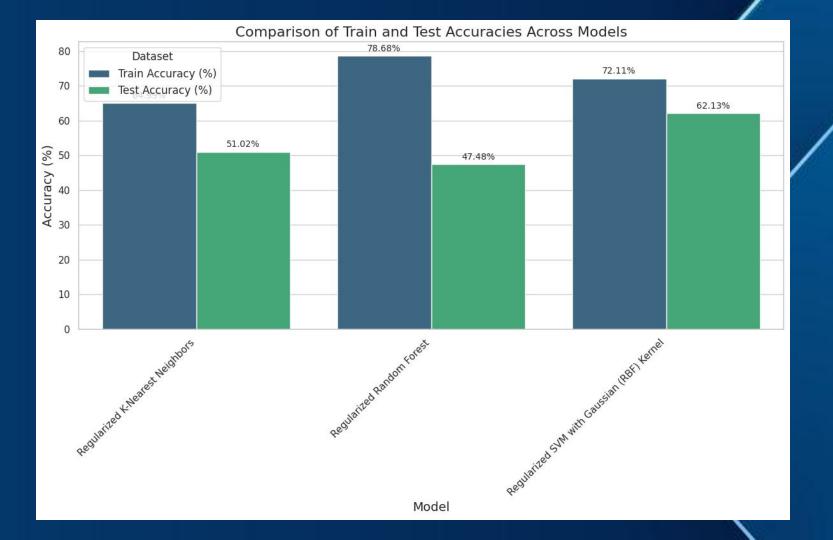
- Train Accuracy: 72.11%
- **Test Accuracy:** 62.13%
- Key Observations:
 - SVM performs better on the test set compared to Random Forest
 - Stronger performance on commands like "right" and "yes"
- Confusion Matrix: Visualized performance for test/train data





Comparison of results

- Model Comparison:
 - KNN: Highest train accuracy, but poor test performance
 - Random Forest: Good on training but overfits on test set
 - SVM: Best test accuracy overall
- Bar Chart: Comparison of Train vs Test accuracy for each model
- **Key Insight:** SVM offers the best balance between training and test performance.



References

- Speech recognition using machine learning techniques. (2024, March 15). IEEE Conference Publication | IEEE Xplore.
 https://ieeexplore.ieee.org/document/10489508
- 2. Automatic Speech Recognition using Advanced Deep Learning Approaches: A survey. (n.d.). Ar5iv. https://ar5iv.org/html/2403.01255
- 3. Speech Recognition Using Machine Learning Techniques. (2024, March 15). IEEE Conference Publication | IEEE Xplore. https://ieeexplore.ieee.org/document/10489508
- 4. Sarbast, H. (2024). Voice Recognition Based on Machine Learning Classification Algorithms: A Review. *Indonesian Journal of Computer Science*, 13(3). https://doi.org/10.33022/ijcs.v13i3.4110

5.