Handwriting for Hope

Scaling Handwriting Analysis for Early Prediction of Alzheimer's Disease with Machine Learning

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Problems and Opportunities

AD leading dementia cause

AD cases expected to triple by 2050

Huge economic impact

$305B cost in 2020, $1.1T projected by 2050

Diagnosis typically happens very late

In the early stages Alzheimer’s symptoms like memory loss and confusion are hard to differentiate from normal aging

Early detection benefits

Slows decline, early access to treatments, future planning

Cost savings with early diagnosis

Reduces costs for families & government, potential $7T savings

Early detection is critical for patient's quality of life & leads to huge cost savings for our society as a whole.

Our Mission

Develop a cost effective and non-invasive ML model that utilizes handwriting samples for early detection of Alzheimer's

Create a platform that utilizes functionality of our model and enable application at scale

Significantly reduce burden on patients, families, and healthcare systems by enabling early intervention

Handwriting analysis shows promise for early identification of Alzheimer's disease risk before major symptoms appear. By detecting Alzheimer's early, we can revolutionize disease management, improve patient outcomes and lead to substantial cost savings

Target Users

People interested in submitting handwriting samples

People concerned about memory issues or early signs of Alzheimer's can submit writing samples to identify risk.

Clinicians interested in early AD prediction

Clinicians can use handwriting analysis to help identify patients at risk for Alzheimer's, and help guide them through different strategies to manage their condition.

AD Scientists

Researchers can access much larger datasets that evolve over time.

Application Overview

User Access

Patients and clinicians can access a web application running Flask on AWS

Data Submission

Patients and clinicians can submit handwriting test results in CSV or JSON format

Data Analysis

A neural net ML model aids in the diagnosis of AD

Results Delivery

Diagnostic predictions are only sent to the clinician. Clinicians discuss the results with the patient.

Data Storage

Handwriting data and scores are stored for model refinement and longitudinal analysis using DynamoDB on AWS


Demo

Journey to Final Model

Dataset Overview

DARWIN

174 participants

Small dataset with 174 participants. There were equal numbers of participants with and without Alzheimer's.

25 tablet tasks

Participants completed 25 different tasks on a tablet device. The tasks fell into 4 main categories: memory, dictation, graphic, and copy.

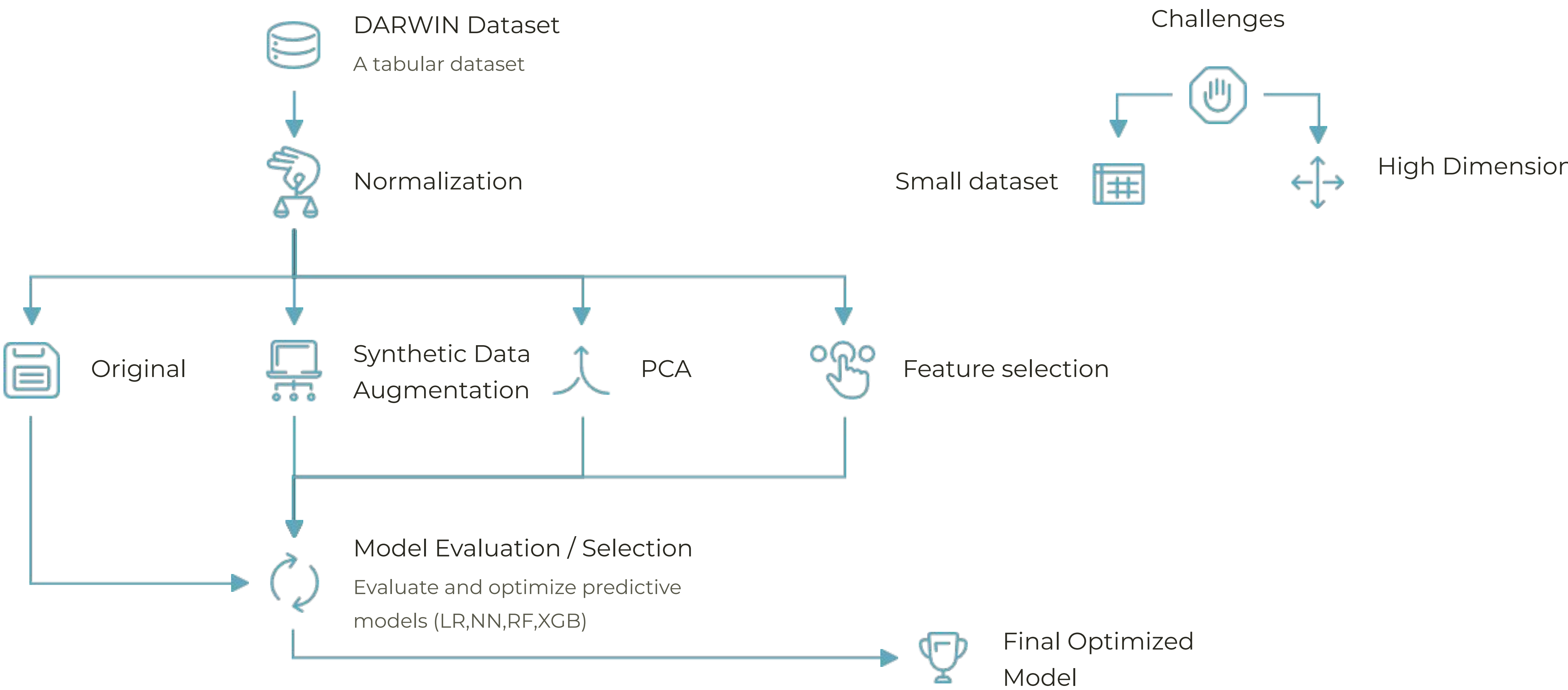
18 feature measurements

For each task, 18 different features were measured, including time to complete task, speed, and acceleration,pressure.

Format

CSV (174,452)

Model Development Process



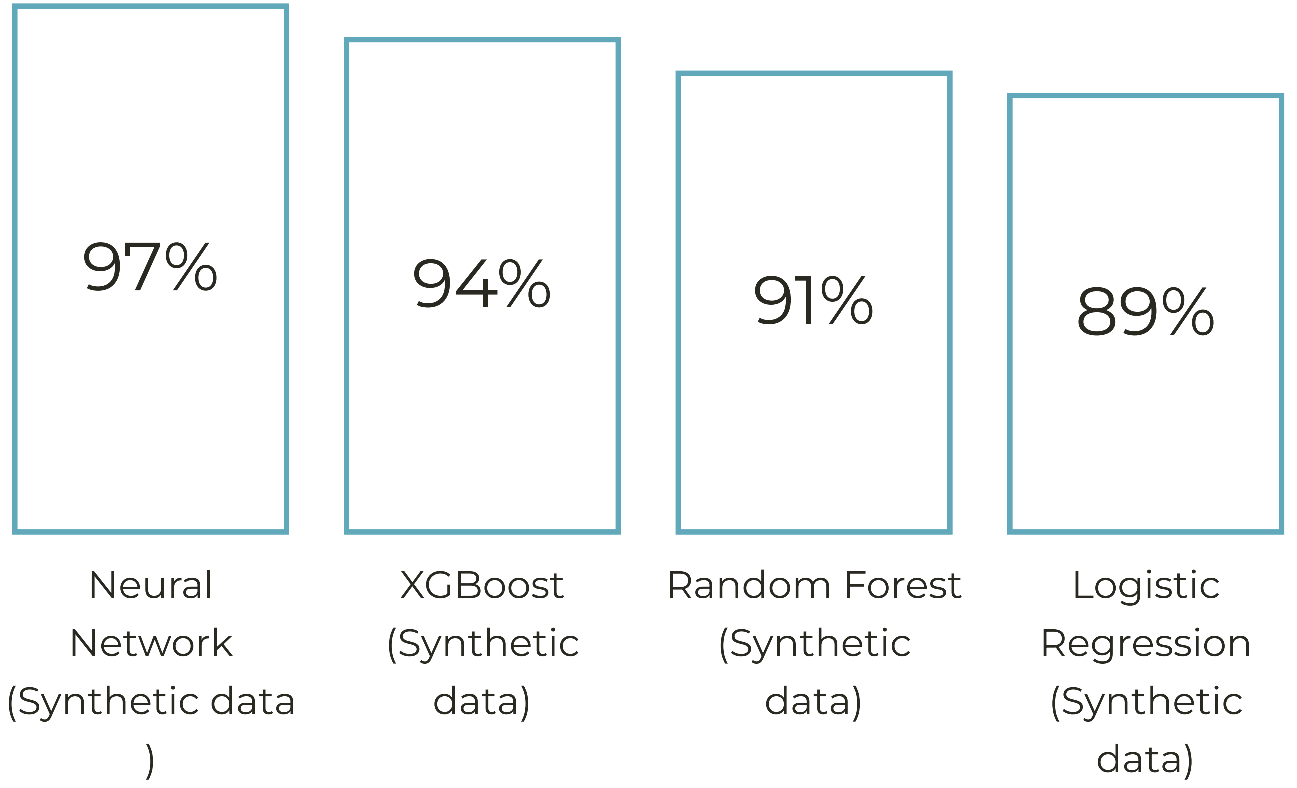
Impact on Model Performance

- *Synthetic data augmentation had the most impact on model performance and improved performance for all models.*
- *PCA and Feature selection had variable results.*

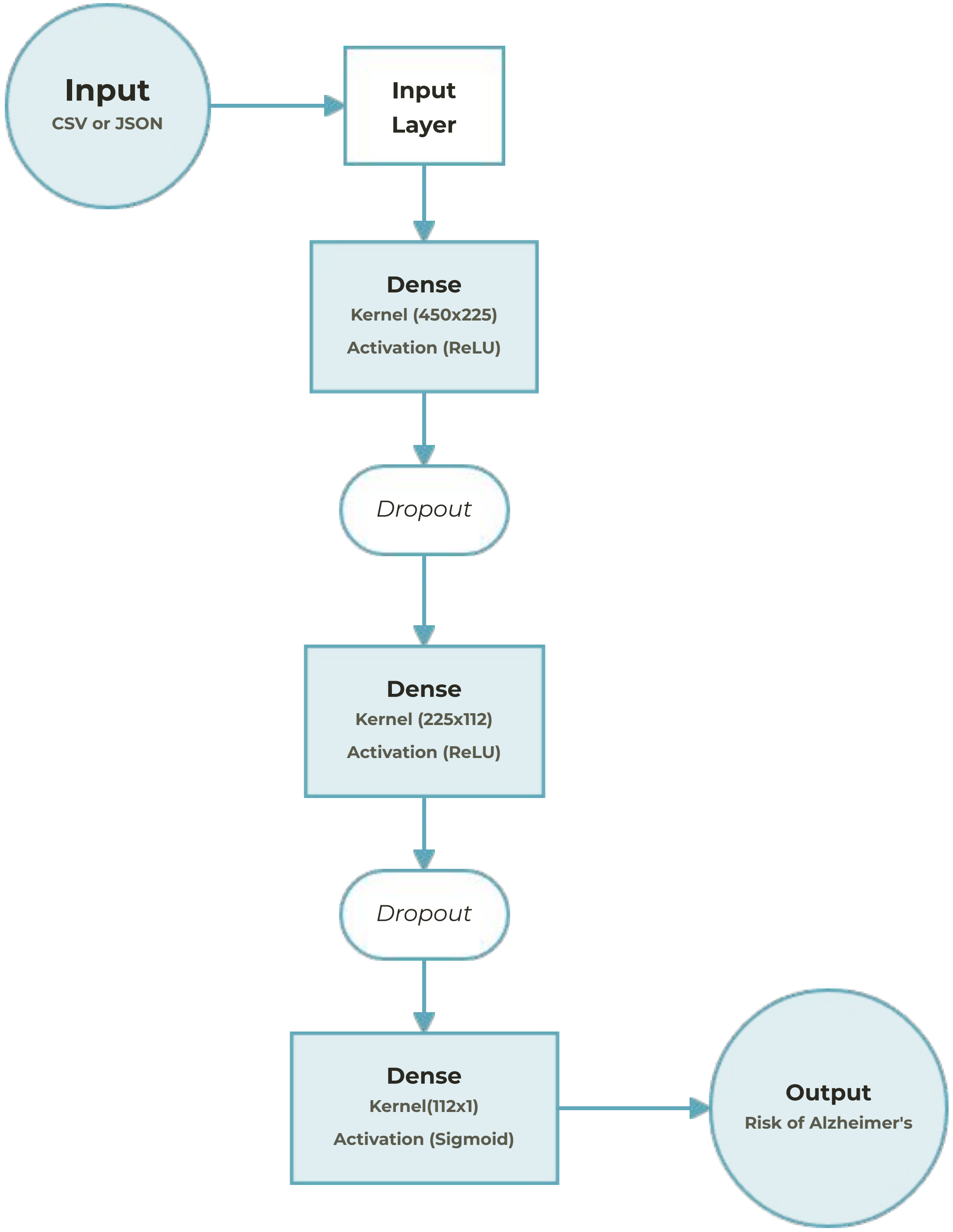
Best Performance For Each Model

Model Performance Measured by

F1 Score



Final Model Architecture (Neural Networks)



DATASET

- ***Expand*** the Handwriting Dataset

  We have reached out to ***researchers*** in our ***healthcare organization*** and **received interest in enrolling participants to use our application**.

- Leverage new data to improve performance of our predictive model.

APPLICATION

- Build an application to extract features from the handwriting tests.

  The application built for the research study is no longer supported.

- Address privacy and security (HIPAA Compliance) concerns of the platform.

Protocol Standardization

- Currently there is no consensus on a standardized protocol for collecting handwriting data.

HANDWRITING FOR HOPE

Appendix

Results from all models

Model	Features	Data	Accuracy	Precision	Recall	F1-Score
Neural Networks	Full Features	Original	0.89	0.87	0.86	0.86
		Augmented	0.97	0.97	0.97	0.97
	Anova	Original	0.83	0.85	0.83	0.83
		Augmented	0.83	0.85	0.83	0.83
	PCA	Original	0.84	0.95	0.94	0.94
		Augmented	0.97	0.97	0.97	0.97
Logistic Regressio n	Full Features	Original	0.83	0.83	0.83	0.83
		Augmented	0.89	0.89	0.89	0.89
	Anova	Original	0.77	0.79	0.77	0.77
		Augmented	0.83	0.83	0.83	0.83
	PCA	Original	0.83	0.83	0.83	0.83
		Augmented	0.89	0.89	0.89	0.89
Random Forest	Full Features	Original	0.89	0.89	0.89	0.89
		Augmented	0.91	0.92	0.92	0.91
	Anova	Original	0.8	0.8	0.8	0.8
		Augmented	0.86	0.87	0.85	0.86
	PCA	Original	0.74	0.83	0.75	0.73
		Augmented	0.89	0.91	0.89	0.88
XG Boost	Full Features	Original	0.83	0.85	0.83	0.83
		Augmented	0.94	0.94	0.94	0.94
	Anova	Original	0.86	0.87	0.85	0.86
		Augmented	0.86	0.86	0.86	0.86
	PCA	Original	0.86	0.87	0.86	0.86
		Augmented	0.94	0.95	0.94	0.94