SIGN LANGUAGE RECOGNITION

PROJECT REPORT (ECS 308: DATA SCIENCE MACHINE LEARNING)

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Github: ***https://github.com/Shirshakk-P/Sign-Language-Recognition***
Dataset: **https://www.mediafire.com/folder/4g3hfsh1egx6m/csv-dataset**

ABSTRACT:

Inability to speak is considered to be true disability and people with this disability use different modes to communicate with others, there are number of methods available for their communication and the most common method is sign language.

American Sign Language is considered as the de-facto standard of sign languages taught all over the world.

Sign Language mainly consists of three major components:

a. **Finger Spelling:** Letter-by-Letter spelling of words during communication.
b. **Word-level Sign Vocabulary:** Majority of communication occurs via word-level signs.
c. **Expressions:** Facial, mouth or bodily expressions make up for some common words in communication.

OBJECTIVES:

This project aims at classifying the several sign language characters (alphabets only) from a set of randomised sign language images using six different Machine Learning Models:

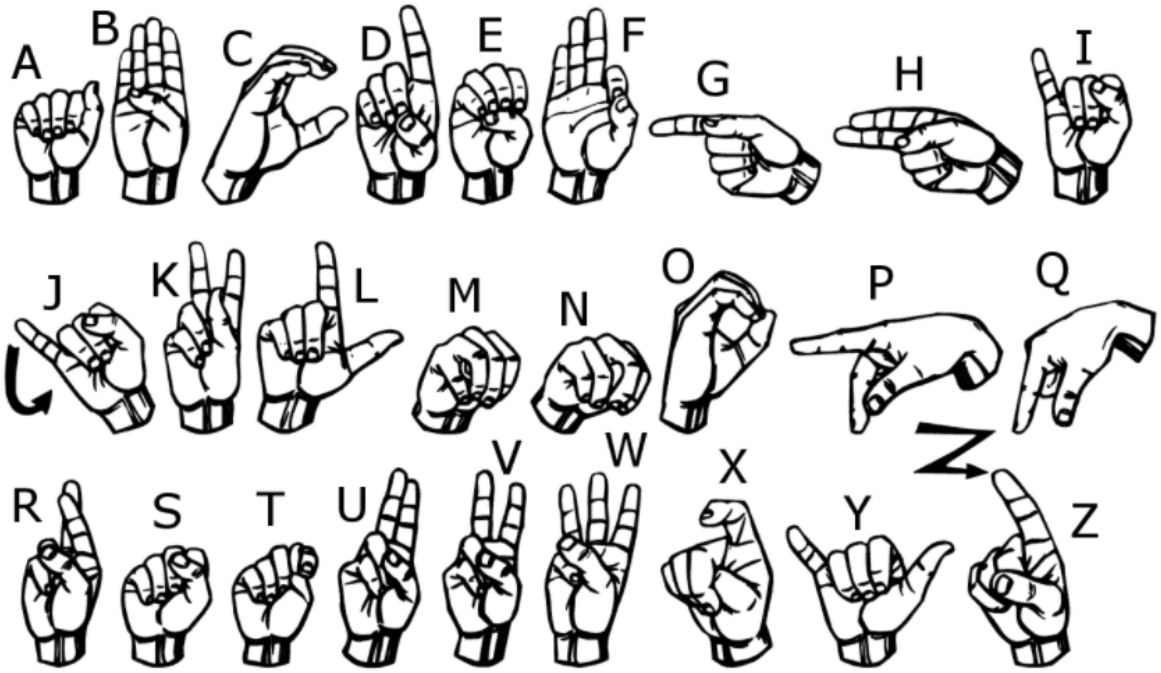
1. **Linear Regression**
2. **Logistic Regression**
3. **Support Vector Machine**
4. **Random Forest**
5. **Convolutional Neural Network**
6. **Artificial Neural Network**

The best accuracies from the combination of these models and respective test_sizes were then compared.

DATASET INFORMATION:

The dataset consisting of the randomised images of American Sign Language characters were converted into the csv dataset files titled:

1. **ASL_train.csv (Training dataset)**
2. **ASL_test.csv (Testing dataset)**



(Representation of the alphabets in American Sign Language)

 # Number of Classes = 25 (0-24)
[The dataset does not contain any symbols for 'J' and 'Z' as they are visually interpreted by motion of the hands similar to 'I' and 'D' respectively]

 # Number of Features = 784

The dataset consists of 25 different categories have been considered for English Alphabets (A-Z), ranging from (0 to 24)

LINEAR REGRESSION MODEL:

We constructed a **Linear Regression model** on the dataset with varying **test_sizes** of **0.20**, **0.25** and **0.30**.

Dataset consisting of a large number of features (784), a low accuracy of around **~70%** was observed.

Error Metric: Mean-Squared Error (MSE)

Observations:

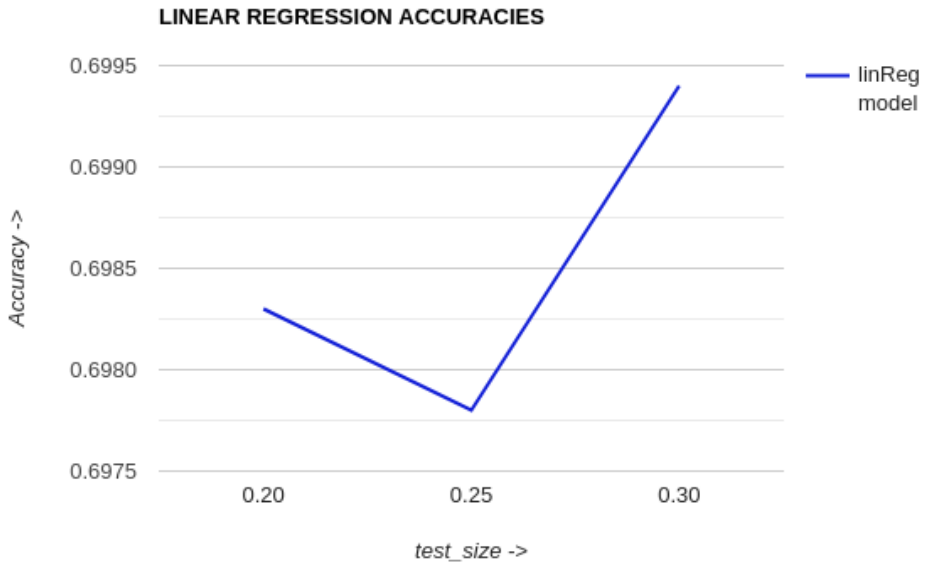
>> Test_size of 0.20 provided an accuracy of 0.6983 with a Mean-squared error of 16.04.

>> Test_size of 0.25 provided an accuracy of 0.6978 with a Mean-squared error of 16.12.

>> Test_size of 0.30 provided an accuracy of 0.6994 with a Mean-squared error of 16.02.

>> Maximum accuracy was found to be 0.6994 at a test_size of 0.30.

Accuracies vs test_size plot:



ANALYSIS:

We constructed a Linear Regression model on the dataset with varying test_sizes of 0.20, 0.25 and 0.30.
Error Metric used was Mean-Squared Error (MSE).

>> Test_size of 0.20 provided an accuracy of 0.6983 with a Mean-squared error of 16.04.
>> Test_size of 0.25 provided an accuracy of 0.6978 with a Mean-squared error of 16.12.
>> Test_size of 0.30 provided an accuracy of 0.6994 with a Mean-squared error of 16.02.

>> Maximum accuracy was found to be 0.6994 at a test_size of 0.30.

MSE being extremely large, this model would not be a good estimator for your purpose.

LOGISTIC REGRESSION MODEL:

We constructed a **Logistic Regression model** on the dataset with varying **test_sizes** of **0.20**, **0.25** and **0.30**.
Dataset consisting of a large number of features (784), a mid-range accuracy of around **~87%** was observed.

Solver Used: Saga (preferred for large datasets)
['**lbfgs**' and '**liblinear**' solvers produced insufficient accuracies]

Observations:

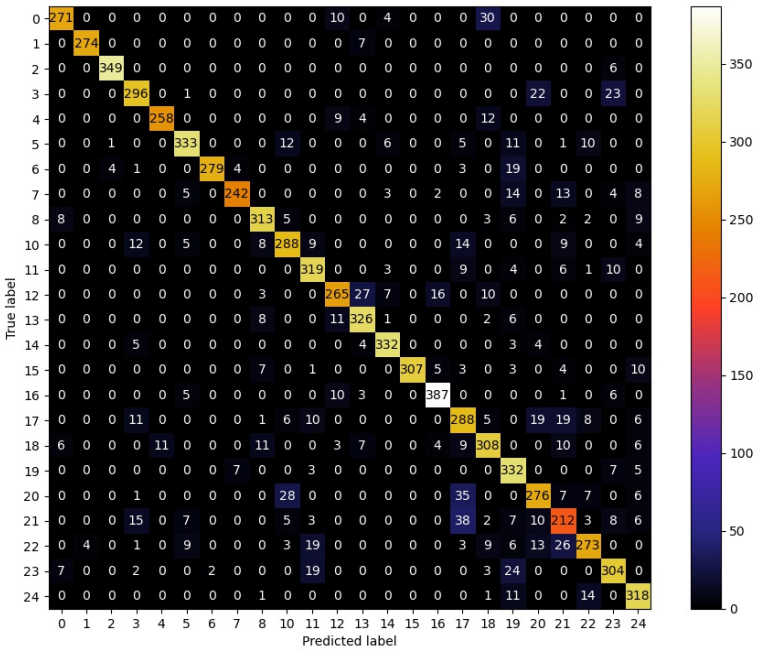
>> Test_size of 0.20 provided an accuracy of 0.8781.

>> Test_size of 0.25 provided an accuracy of 0.8766.

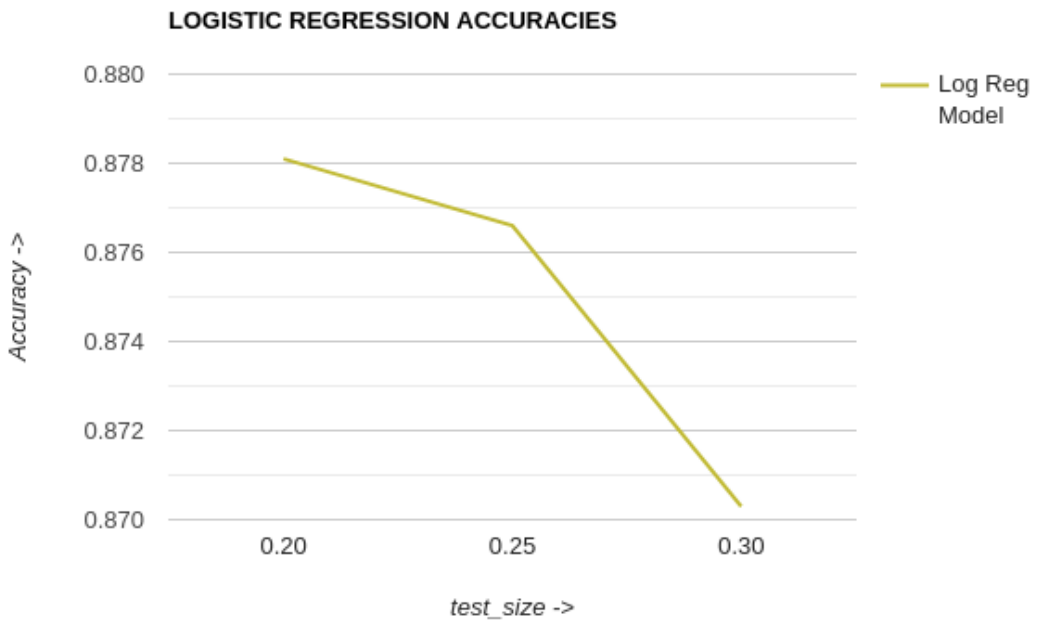
>> Test_size of 0.30 provided an accuracy of 0.8703.

>> Maximum accuracy was found to be 0.8781 at a test_size of 0.20.

Confusion Matrix: **LOGISTIC REGRESSION**



Accuracies vs test_size plot:



ANALYSIS:

Also, our necessity is for a probabilistic value for classification, but Linear Regression provides us with continuous value.
We constructed a Logistic Regression model on the dataset with varying test_sizes of 0.20, 0.25 and 0.30.

>> Test_size of 0.20 provided an accuracy of 0.8781.
>> Test_size of 0.25 provided an accuracy of 0.8766.
>> Test_size of 0.30 provided an accuracy of 0.8703.

>> Maximum accuracy was found to be 0.8781 at a test_size of 0.20.

'Saga' solver was used that is in general preferred for large datasets. Along with L1 penalty, it supported the 'elasticnet' property.
'lbfgs' and 'liblinear' solvers produced insufficient accuracies.

SUPPORT VECTOR MACHINE MODEL:

We constructed a **Support Vector Machine model** on the dataset with varying **test_sizes** of **0.20**, **0.25** and **0.30**.

Dataset consisting of a large number of features (784), an extremely high accuracy of around **~99%** was observed, which was discovered to be the case of **Over-fitting**.

Shape of Decision Function: **One-vs-one (ovo)**

Gamma Value: **0.0001**

One-vs-one ('ovo') was chosen as the shape of the decision function due to the nature of dataset being multi-class classification and ‘rbf’ (radial basis function) as the kernel. Kernels (‘linear’ and ‘poly’) had high execution times (>35 min).

Any gamma value > pow(10,-3) had extremely high runtimes. The decision boundary is observed to have lesser curvature with gamma < pow(10,-3).

Observations:

>> Test_size of 0.20 provided an accuracy of 0.9998.

>> Test_size of 0.25 provided an accuracy of 0.9972.

>> Test_size of 0.30 provided an accuracy of 0.9969.

>> Maximum accuracy was found to be 0.9998 at a test_size of 0.20.

ANALYSIS:

We constructed a Support Vector Machine model on the dataset with varying test_sizes of 0.20, 0.25 and 0.30.

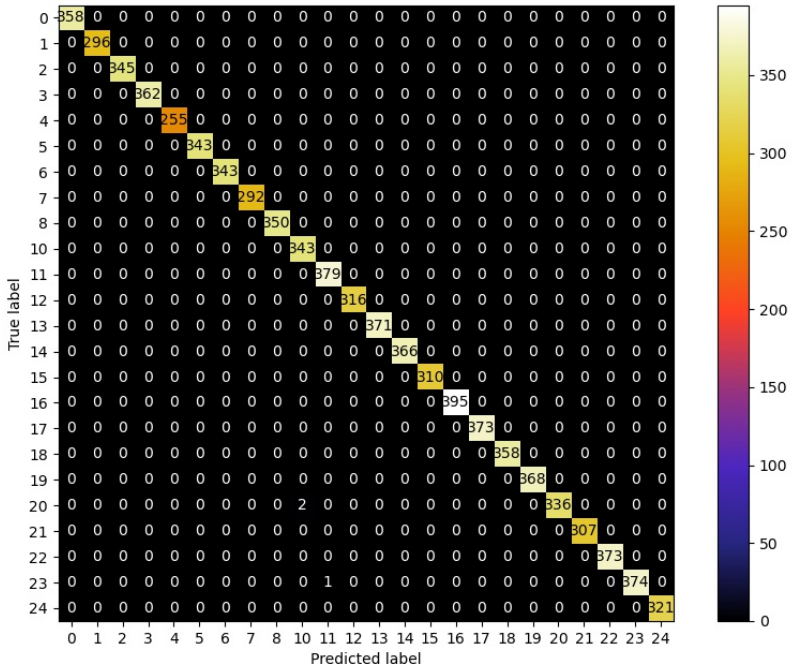
>> Test_size of 0.20 provided an accuracy of 0.9998.
>> Test_size of 0.25 provided an accuracy of 0.9972.
>> Test_size of 0.30 provided an accuracy of 0.9969.

>> Maximum accuracy was found to be 0.9998 at a test_size of 0.20.

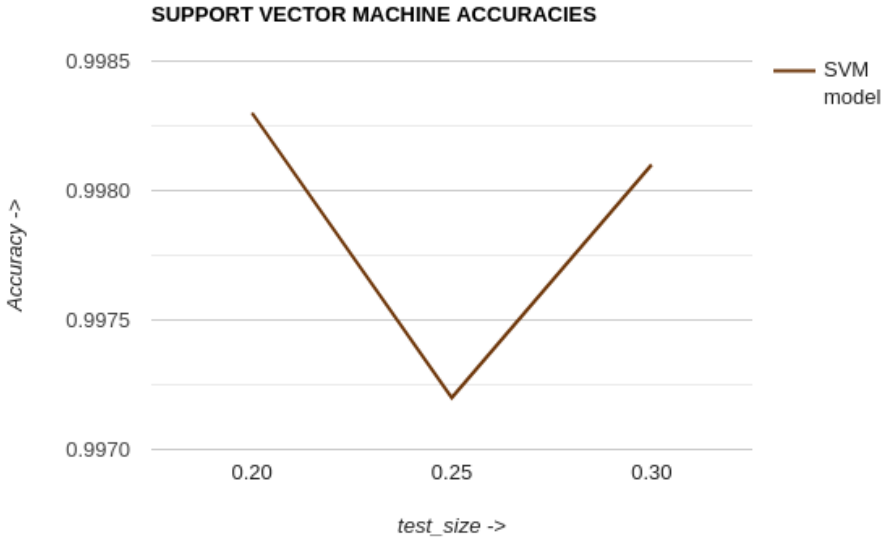
One-vs-one ('ovo') was chosen as the shape of the decision function due to the nature of dataset being multiclass classification and ‘rbf’ (radial basis function) as the kernel. Kernels (‘linear’ and ‘poly’) had high execution times (>35 min on local machine).

Any gamma value > pow(10,-3) had extremely high runtimes. The decision boundary is observed to have lesser curvature with gamma < pow(10,-3).

Confusion Matrix: **SUPPORT VECTOR MACHINE**



Accuracies vs test_size plot:



RANDOM FOREST MODEL:

We constructed a **Random Forest model** on with **100 estimators** and varying **test_sizes** of **0.20**, **0.25** and **0.30**.
Dataset consisting of a large number of features (784), an extremely high accuracy of around **~99%** was observed.

This model with the help of 100 Decision Trees used averaging to improve the predictive accuracy and solved the problem of **Overfitting** observed in **SVM model**.

Observations:

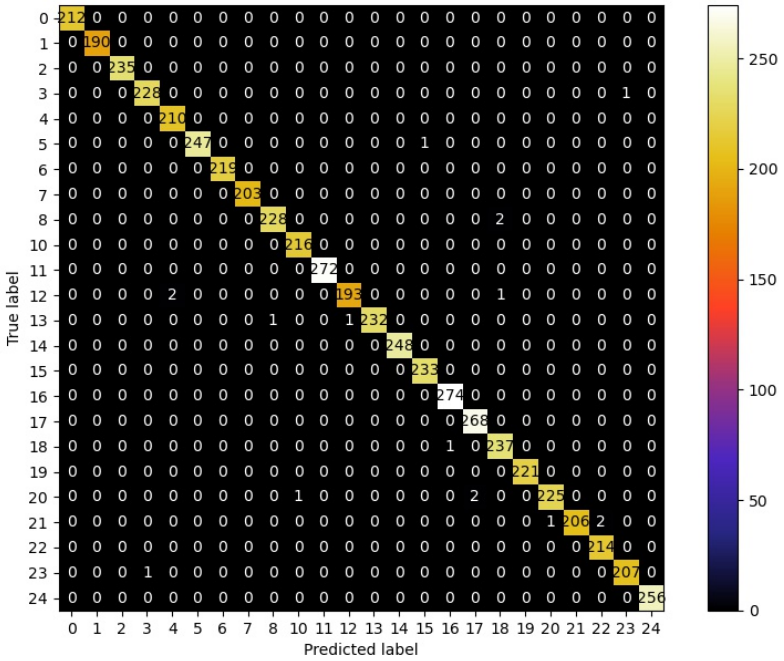
>> Test_size of 0.20 provided an accuracy of 0.9974.

>> Test_size of 0.25 provided an accuracy of 0.9972.

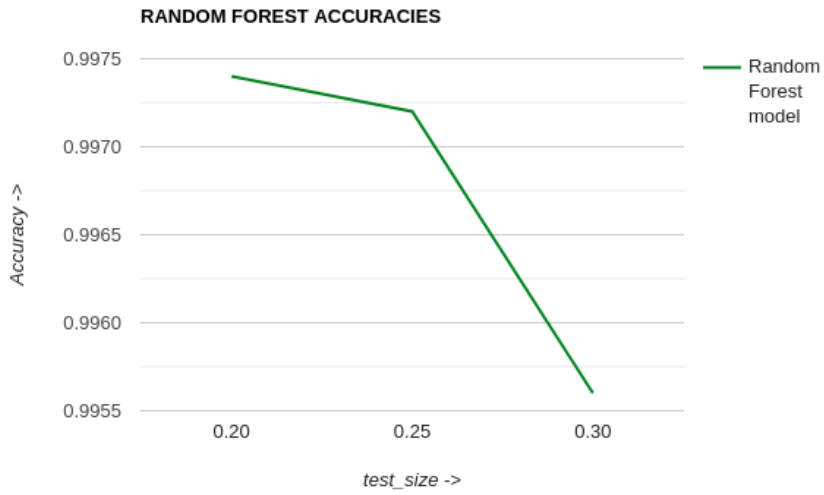
>> Test_size of 0.30 provided an accuracy of 0.9956.

>> Maximum accuracy was found to be 0.9998 at a test_size of 0.20.

Confusion Matrix: RANDOM FOREST MODEL



Accuracies vs test_size plot:



ANALYSIS:

We constructed a Random Forest model on with 100 estimators and varying test_sizes of 0.20, 0.25 and 0.30.

>> Test_size of 0.20 provided an accuracy of 0.9974.
>> Test_size of 0.25 provided an accuracy of 0.9972.
>> Test_size of 0.30 provided an accuracy of 0.9956.

>> Maximum accuracy was found to be 0.9998 at a test_size of 0.20.

The random forests model calculates a response variable by creating many different decision trees and then putting each object to be modeled down each of the decision trees, which is determined by evaluating the responses from all of the trees.

This model with the help of 100 Decision Trees used averaging to improve the predictive accuracy and solved the problem of overfitting observed in SVM model with an accuracy of ~99.6%

UNSUPERVISED LEARNING: **Convolutional Neural Network (CNN)**

We constructed a **Convolutional Neural Network model** on the dataset that comprised of **three Convolution Layers** (consisting of **128**, **64** and **32 units** respectively) and **three MaxPooling Layers** (of **window-size 3*3** , **2*2** and **2*2** respectively).

Activation Function: **ReLU**

Model Summary:

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 128)	3328
max_pooling2d (MaxPooling2D)	(None, 14, 14, 128)	0
conv2d_1 (Conv2D)	(None, 14, 14, 64)	32832
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 64)	0
conv2d_2 (Conv2D)	(None, 7, 7, 32)	8224
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 32)	0
flatten (Flatten)	(None, 512)	0
dense (Dense)	(None, 512)	262656
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 24)	12312

Total params: 319,352
Trainable params: 319,352
Non-trainable params: 0

Observations:

>> Accuracy was found to be 0.9297267198 after 35 epochs of batch_size 138.

The benefit derived by using CNNs here is due to their ability to develop an internal representation of a two-dimensional image, the model learns the position and scale in variant structures in the data, which is extremely essential while dealing with images.

ANALYSIS:

We constructed a Convolutional Neural Network model on the dataset that comprised of three Convolution Layers (consisting of 128, 64 and 32 units respectively) and three MaxPooling Layers (of window-size 3*3 , 2*2 and 2*2 respectively).

Activation Function: ReLU
Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 128)	3328
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max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 32)	0
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NEURAL NETWORK MODEL: **Artificial Neural Network (ANN)**

We constructed an **Artificial Neural Network model** on the dataset with varying **test_sizes** of **0.20**, **0.25** and **0.30**.

The ANN model consisted of:

1. A ***"Dense"*** layer of 300 units followed by a ***"Dropout"*** layer of **rate 0.3**. **(*Activation function: ReLU*)**

2. Three sets of ***"Dense"*** layers consisting of 100 units each. **(*Activation function: ReLU*)**

3. A final ***"Dense"*** layer with 25 units. **(*Activation function: Softmax*)**

Dataset consisting of a large number of features (784),a high accuracy of around **~97%** was observed.

Activation Functions: **ReLU, Softmax**

Loss Metric: **Categorical Cross-Entropy** *(multi-class classification problem)*

Optimizer: **Nadam** *(provided the optimal accuracy)*

Model Summary:

```
model = Sequential(Flatten(input_shape = [28, 28]))
model.add(Dense(300, activation='relu'))
model.add(Dropout(rate= 0.3))
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(100, activation='relu'))
model.add(Dense(25, activation='softmax'))
model.compile(loss='sparse_categorical_crossentropy', optimizer='nadam',
                  metrics='accuracy')
h = model.fit(X_train, y_train, epochs=6, verbose=True)
```

Observations:

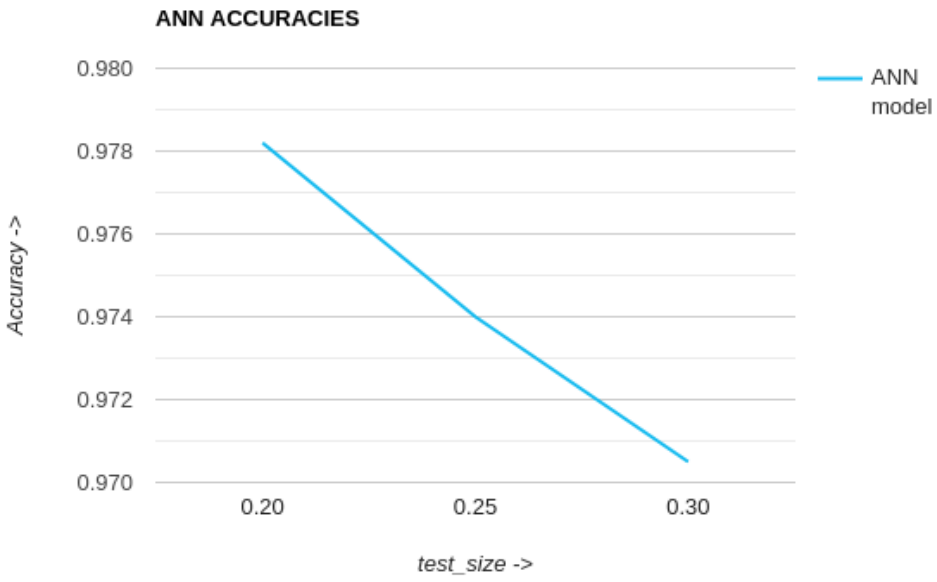
>> Test_size of 0.20 provided an accuracy of 0.9781.

>> Test_size of 0.25 provided an accuracy of 0.9740.

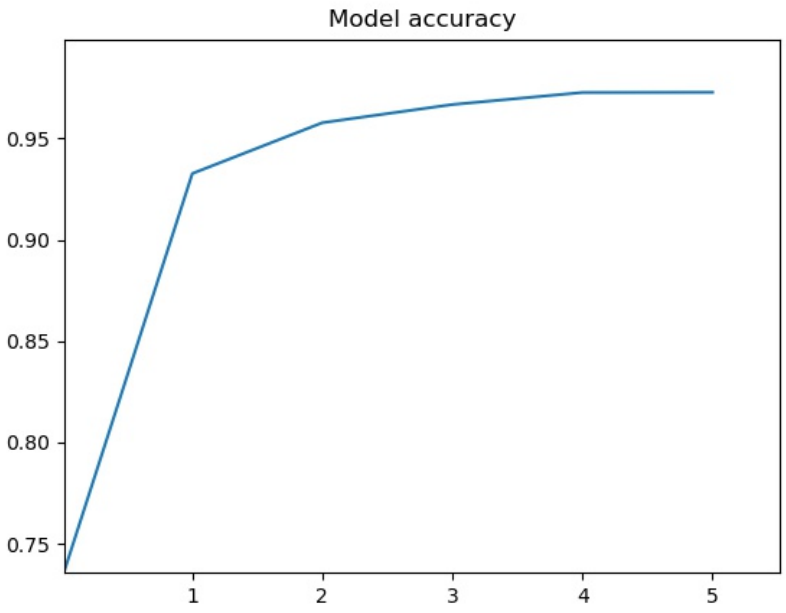
>> Test_size of 0.30 provided an accuracy of 0.9705.

>> Maximum accuracy was found to be 0.9781 at a test_size of 0.20 after 6 epochs.

Accuracies vs test_size plot:



Accuracies vs Epoch plot:



ANALYSIS:

We constructed an Artificial Neural Network model on the dataset with varying test_sizes of 0.20, 0.25 and 0.30.

The ANN model consisted of:
1. A "Dense" layer of 300 units followed by a "Dropout" layer of rate 0.3. (Activation function: ReLU)
2. Three sets of "Dense" layers consisting of 100 units each.(Activation function: ReLU)
3. A final "Dense" layer with 25 units. (Activation function: Softmax)

Activation Functions: ReLU, Softmax
Loss Metric: Categorical Cross-Entropy
Optimizer: Nadam

>> Test_size of 0.20 provided an accuracy of 0.9781.
>> Test_size of 0.25 provided an accuracy of 0.9740.
>> Test_size of 0.30 provided an accuracy of 0.9705.

>> Maximum accuracy was found to be 0.9781 at a test_size of 0.20 after 6 epochs.

We use 'sparse_categorical_crossentropy' as the loss function as the problem is multi-class classification problem. 'Nadam' optimizer is used as it provided the optimal accuracy.

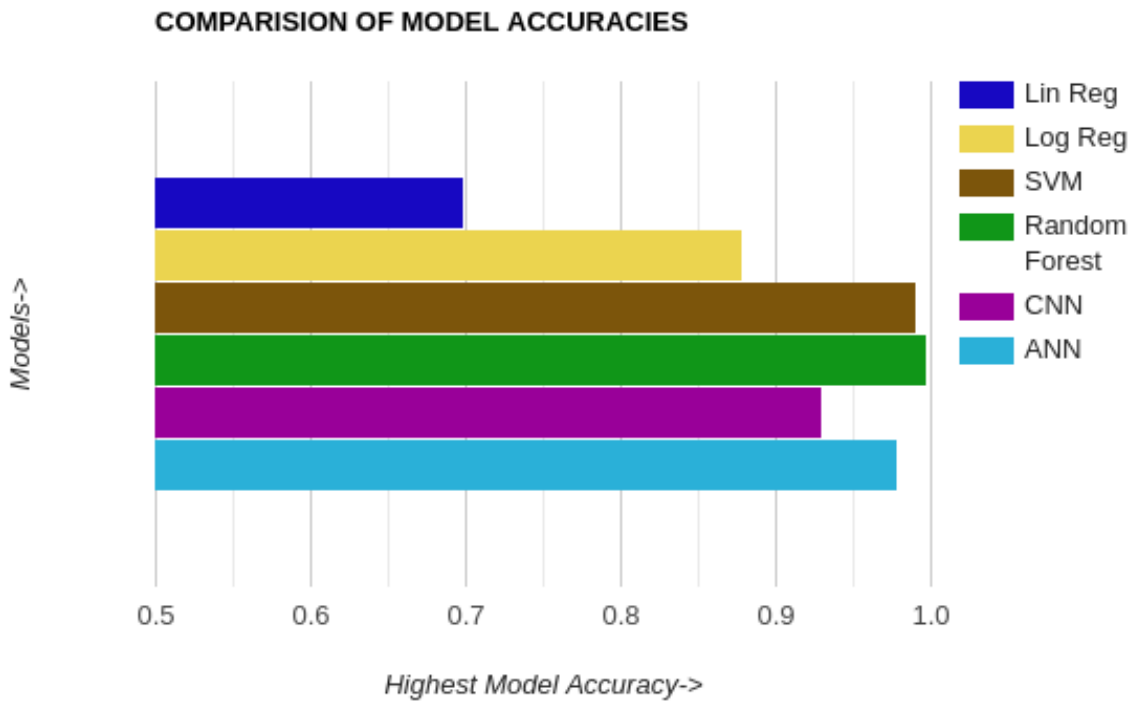
MODEL COMPARISONS: **(Models w.r.t. test_sizes)**

Model Accuracy:	test_size = 0.20	test_size = 0.25	test_size = 0.30
Linear Regression	0.6983	0.6978	0.6994
Logistic Regression	0.8781	0.8766	0.8703
SVM	0.9998	0.9972	0.9969
Random Forest	0.9974	0.9972	0.9956
ANN	0.9781	0.9740	0.9705

>> Maximum accuracy was found out from the SVM Model with test_size of 0.20 (OVERFITTING).

>> Minimum accuracy was found out from the Linear Regression Model with test_size of 0.20.

Comparative Representation of the Model Accuracies:



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1.American Sign Language Character Recognition Using Convolution Neural Network (https://link.springer.com/chapter/10.1007/978-981-10-5547-8_42)

2.https://data-flair.training/blogs/sign-language-recognition-python-ml-opencv/

3.https://debuggercafe.com/american-sign-language-detection-using-deep-learning/

4.https://stats.stackexchange.com/questions/52773/what-can-cause-pca-to-worsen-results-of-a-classifier.

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