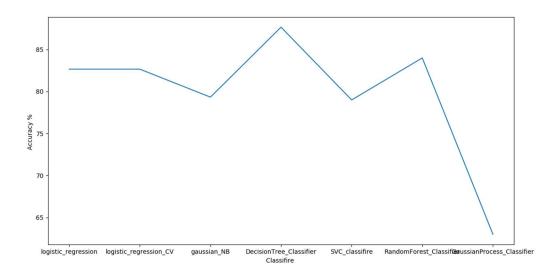
Classifier used

- LogisticRegressionCV
- DecisionTreeClassifier
- LogisticRegression
- GaussianNB
- RandomForestClassifier
- SVC
- GaussianProcessClassifier
- ANN

Accuracy graph:



With ANN we got atmax 76 %. I used Tensorflow grid search for getting accuracy for different hyper-parameters.

Due to lack of time and hardware availability I wasn't able to try many permutations in Grid Serch.

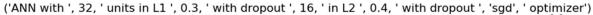
```
adef ANN_with_gridSearch(X_train, X_test, y_train, y_test):
    HP_MUM_UNITS_1 = hp.HParam('num_units_1', hp.Discrete(list(range(32,33))))
    HP_DROPOUT_1 = hp.HParam('dropout_1', hp.RealInterval(0.3, 0.4))
    HP_NUM_UNITS_2 = hp.HParam('num_units_2', hp.Discrete(list(range(16,17))))
    HP_DROPOUT_2 = hp.HParam('dropout_2', hp.RealInterval(0.3, 0.4))
    HP_OPTIMIZER = hp.HParam('optimizer', hp.Discrete(['adam','sgd']))
    METRIC_ACCURACY = 'accuracy'
    hparams=[HP_NUM_UNITS_1, HP_DROPOUT_1, HP_NUM_UNITS_2, HP_DROPOUT_2, HP_OPTIMIZER]
    hparams=[HP_NUM_UNITS_1, HP_NUM_UNITS_2, HP_OPTIMIZER]
    metrics=[hp.Metric(METRIC_ACCURACY, display_name='Accuracy')]
```

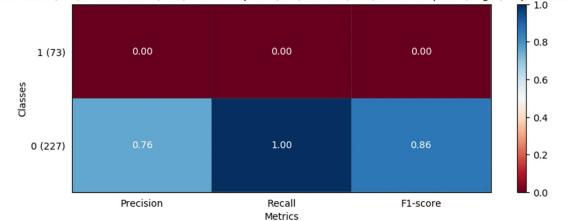
As shown in figure, 2 layers are used and in both layers have used Dropout regularization (instead of L2- Frohenius regularization). Also we can state range of units in hidden layers in it. Have tried it on 2 optimizers and Adams was giving more accuracy.

```
def train_test_model(hparams,X_train,X_test, y_train, y_test):
    model = tf.keras.models.Sequential([
        tf.keras.layers.Dense(hparams['num_units_1'], activation=tf.nn.relu),
        tf.keras.layers.Dropout(hparams['dropout_1']),
        #tf.keras.layers.Dense(hparams['num_units_2'], kernel_regularizer=keras.regularizers.l2(0.1), activation=tf.nn.relu),
        tf.keras.layers.Dense(hparams['num_units_2'], activation=tf.nn.relu),
        tf.keras.layers.Dense(hparams['dropout_2']),
        tf.keras.layers.Dense(1, activation=tf.nn.sigmoid),
        tf.keras.layers.Platten()
])
```

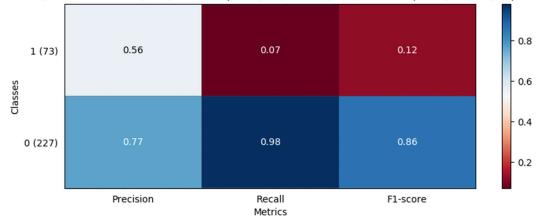
As shown in above figure, we can also use other regularization technique. (commented out lines)

Classification report for different Classifiers:

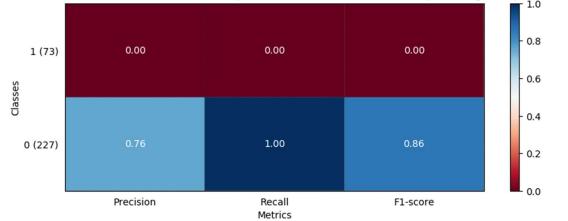




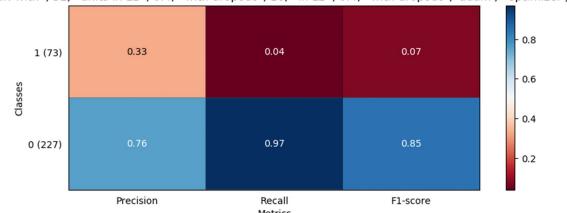
('ANN with ', 32, ' units in L1 ', 0.4, ' with dropout ', 16, ' in L2 ', 0.3, ' with dropout ', 'adam', ' optimizer')



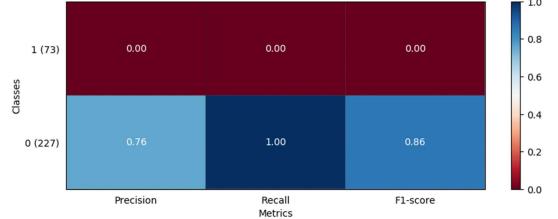
('ANN with ', 32, ' units in L1 ', 0.4, ' with dropout ', 16, ' in L2 ', 0.3, ' with dropout ', 'sgd', ' optimizer')

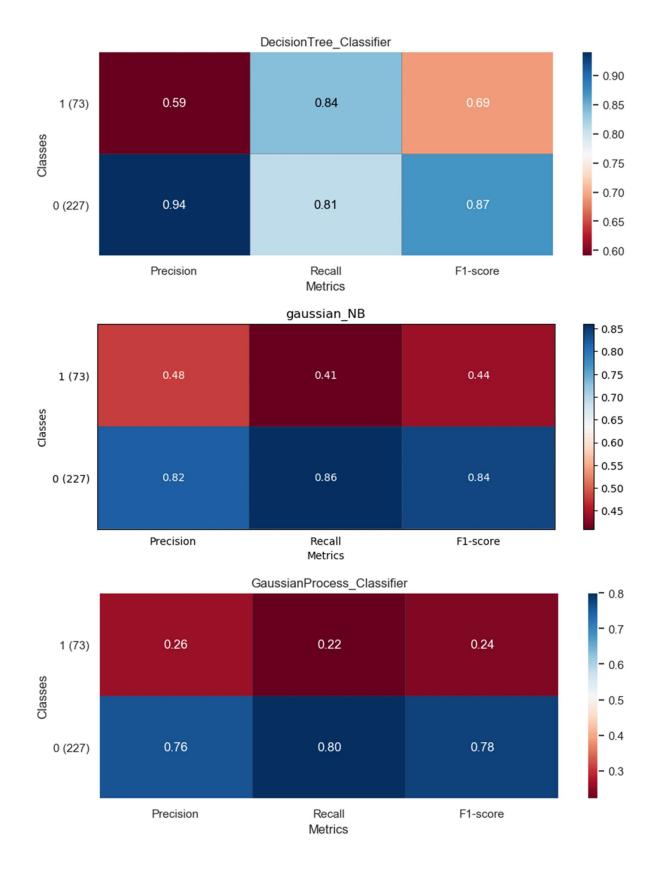


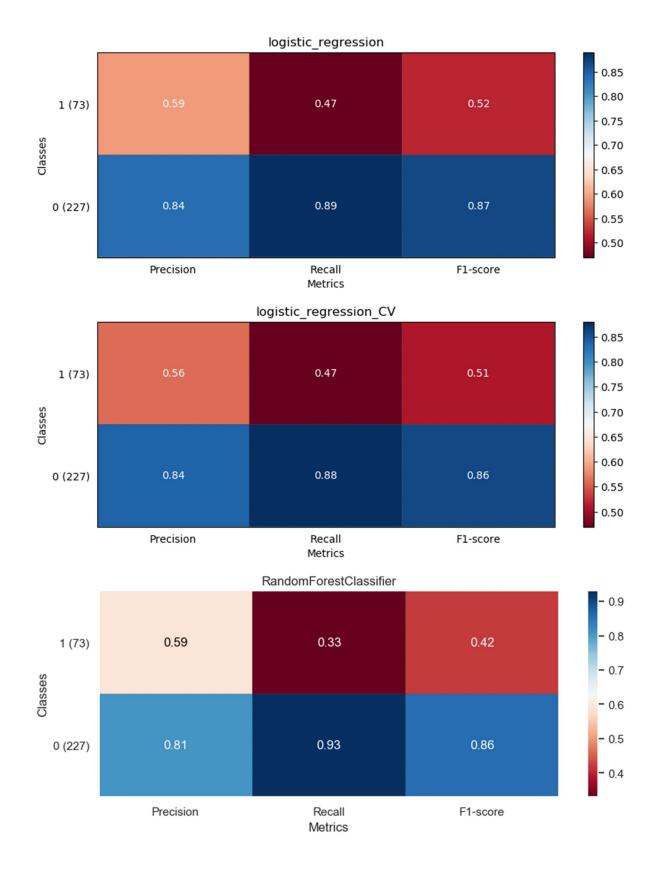
('ANN with ', 32, ' units in L1 ', 0.4, ' with dropout ', 16, ' in L2 ', 0.4, ' with dropout ', 'adam', ' optimizer')

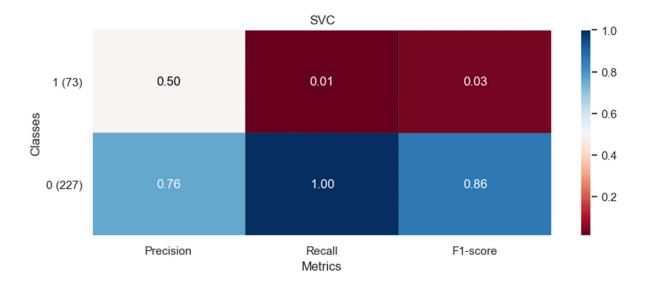


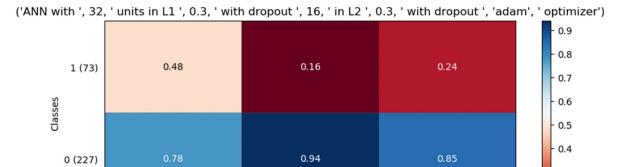
('ANN with ', 32, ' units in L1 ', 0.4, ' with dropout ', 16, ' in L2 ', 0.4, ' with dropout ', 'sgd', ' optimizer')











Recall

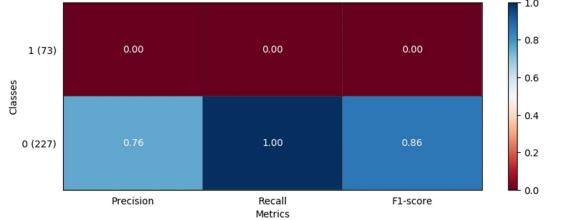
Metrics

Precision

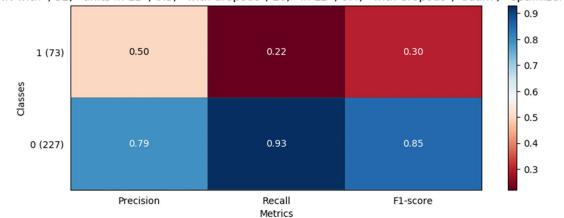
- 0.3

F1-score



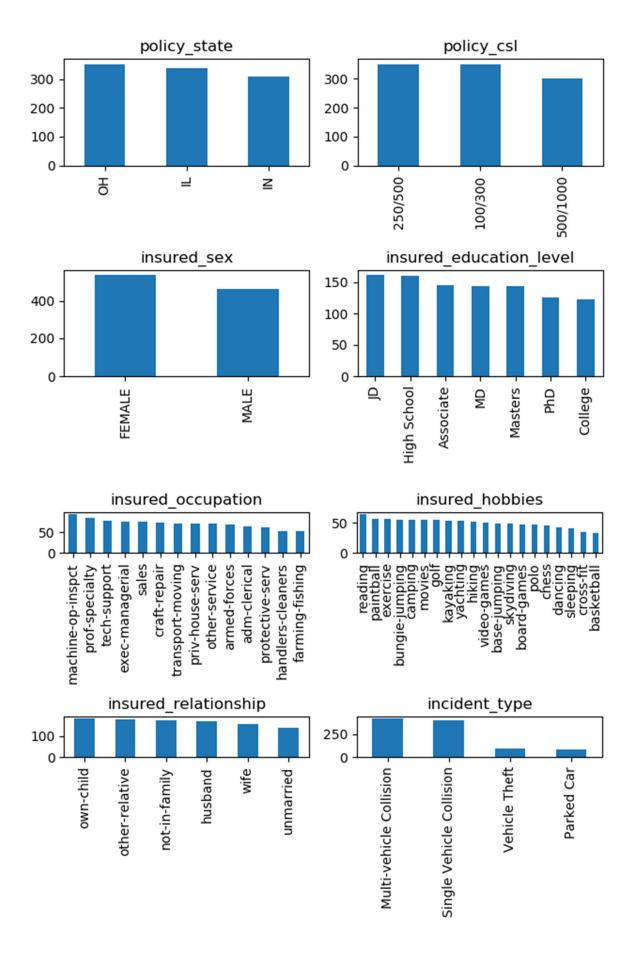


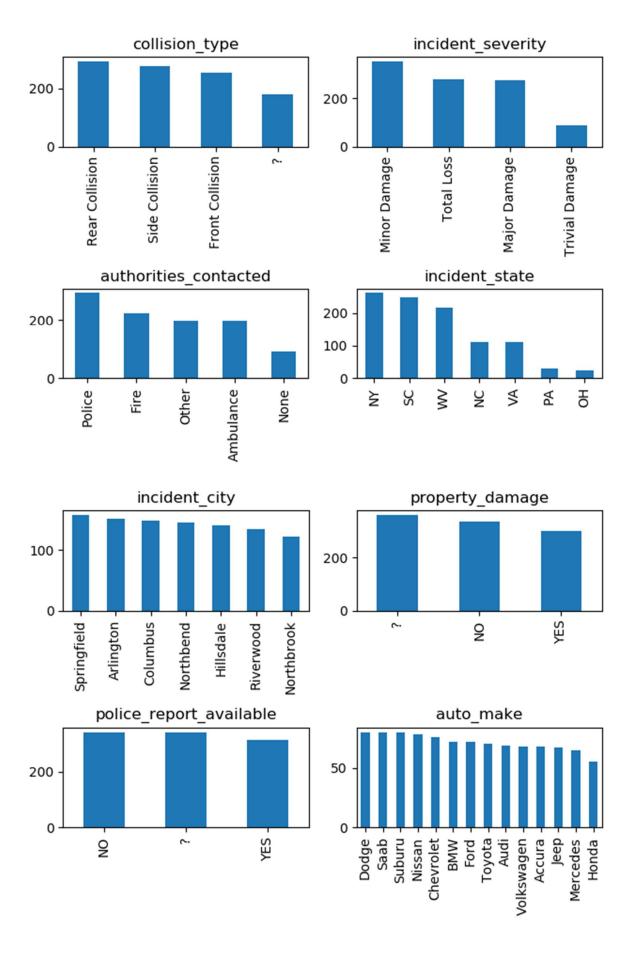
('ANN with ', 32, ' units in L1 ', 0.3, ' with dropout ', 16, ' in L2 ', 0.4, ' with dropout ', 'adam', ' optimizer')

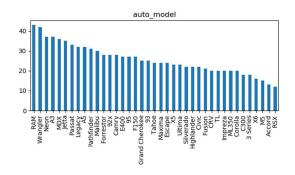


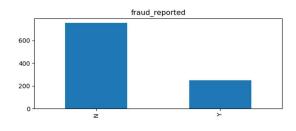
Now data visualization of all features

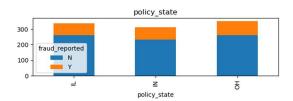


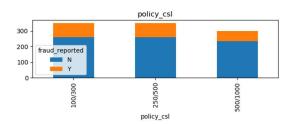


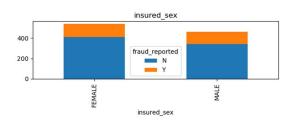


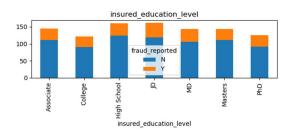








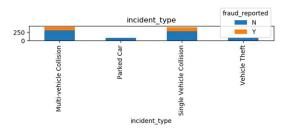


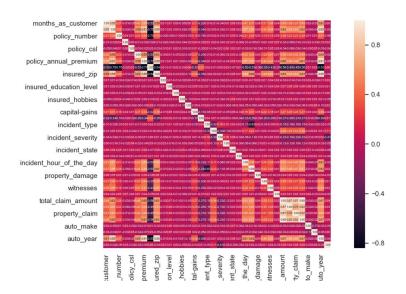




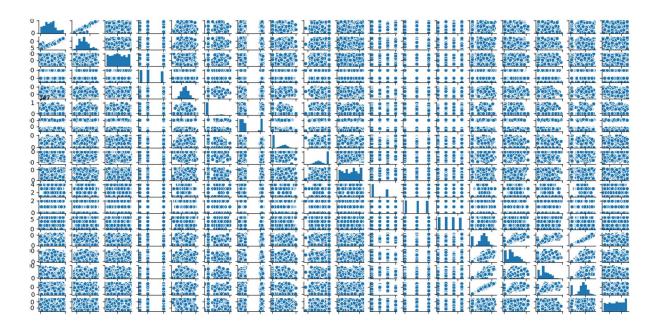








Pairplot



Have used Label encoder to encode features:

```
le = preprocessing.LabelEncoder()
for column in col_ob_dt:
   insurance_csv[column] = le.fit_transform(insurance_csv[column].astype(str))
   print(column,' ',le.classes_)
```

Normalizing data for greater performance

```
adef preprocess_data(insurance_csv,col_ob_dt):
    col_to_normalize = list( set(insurance_csv.columns) - set(col_ob_dt))
    insurance_csv[col_to_normalize] = preprocessing.normalize(insurance_csv[col_to_normalize])
    insurance_csv.to_csv('Sample1.csv')
    return insurance_csv
```

FUTURE scope:

- To have positive correct matrix
- To use OverSampling since we have less data
- To try more NN schema and hyper parameters with Oversampling