# 4. Results

The model’s functions, model predictions, analysis and results are discussed in this section.

## 4.1 Logistic regression scatterplot

Looking at the confusion matrix of the logistic regression model, we can see that it makes a lot of correct predictions as evidenced by the diagonal line for all true positive instances. But as evidenced by the number of predictions outside the diagonal line, the model also has a lot of false positive and negative instances. The number of correct and incorrect predictions seems to be almost even, with more correct predictions.

A white background with blue squares

Description automatically generated with medium confidence

Figure : Logistic regression scatterplot

## 4.2 Support Vector Scatterplot

Now we see that for both SVM models, the confusion matrix is a lot cleaner than the Logistic Regression Model. The models' higher accuracy, precision, recall and f1 scores is evidenced by the strong diagonal line going through the confusion matrix. Although better, these models still have some false negative and positive instances as shown by the number of predictions outside the diagonal line. Even with the high scores, we can see that both models often confuse similar classes, leading to higher false negative predictions. This is clearly seen in the data for the 'MO' state, which while having a relatively high number of correct predictions, the mistakes it makes are all for similar classes.

A screenshot of a computer screen

Description automatically generated

Figure : Support Vector Scatterplot

## 4.3 Naïve Bayes

Inspection of the Naive Bayes confusion matrix reveals it is the worst performing model on this task by a significant margin. Unlike classifiers such as the neural network, there is no clear diagonal trace of correct predictions. Instead, the matrix shows a fractured scattering of both accurate and obviously incorrect labels. For certain classes, Naive Bayes functions reasonably well, evidenced by small clusters along the central diagonal. However, its performance completely deteriorates on other subsets of the data. We see predictions are randomly spread across incorrect output categories rather than focused on the true labelsA white and blue background with many small squares

Description automatically generated with medium confidence

Figure : Naive bayes scatterplot

## 4.4a Custom Neural Network (Test)

Analysis of the confusion matrices for our custom neural network reveals it has achieved the cleanest, most well-defined predictions out of all models tested. Examining the training and testing confusion matrices, we see very clear diagonal lines indicating correct label predictions. This diagonal pattern appears equally strong in both the training and testing results. The similar diagonals demonstrate our neural network has learned robust patterns in the data rather than overfitting on features of the training set.

Although some incorrect predictions exist outside the main diagonal, the number of errors is lower compared to alternative models such as support vector machines. Additionally, the incorrect predictions follow an orderly structure. Mistakes tend to confuse similar classes rather than spreading randomly across unrelated labels. This indicates the network learns meaningful representations to discriminate between close output categories related to income and cost of living. While there is occasionally confusion between adjacent classes, there are very few isolated errors falsely predicting back-to-back dissimilar classes.A blue and white grid with a line in the middle

Description automatically generated with medium confidence

Figure a: Custom neural Network (Test)

## 4.4b Custom Neural Network (Training)

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Description automatically generated with medium confidence

Figure 4b: Custom Neural Network (Training)

## 4.5 Model Comparison

The results in table (1) shows that the custom neural network model achieved the highest accuracy (0.93), precision (0.93), recall (0.93) and F1 score (0.93) on this task. This indicates the neural network had the best overall predictive performance on the income and cost of living data. In comparison, the other models - logistic regression, support vector classifier, and Naive Bayes - had significantly lower predictive performance according to these evaluation metrics. The Naive Bayes classifier performed particularly poorly, only achieving an accuracy and F1 score of 0.25 and 0.24 respectively. The support vector classifier attained moderately good precision, recall, and F1 compared to the other non-neural network models. But the custom neural network still markedly outperformed all other approaches. This suggests that deep learning models may have advantages in effectively modeling complex relationships in socioeconomic data.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Accuracy (%) | Precision (%) | Recall (%) | F1 score (%) |
| Logistic regression | 0.59 | 0.59 | 0.59 | 0.59 |
| Support Vector Classifier | 0.84 | 0.85 | 0.84 | 0.84 |
| Naïve Bayes | 0.25 | 0.30 | 0.25 | 0.24 |
| Custom Neural Network | 0.93 | 0.93 | 0.93 | 0.93 |

Table : Model comparison

# Appendix

A graph of a function

Description automatically generated with medium confidence

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