Report on ANN Performance and Implementation Challenges

Overall Performance of the ANN

The performance of the Artificial Neural Network (ANN) was evaluated using metrics such as accuracy, precision, recall, F1-score, and the confusion matrix. The results indicated that the model is predicting all test samples as positive reviews, leading to the following observations:

- **Accuracy:** 50.20%, indicating that the model's performance is equivalent to random guessing.
- **Precision:** 0.50, reflecting that only half of the positive predictions are correct.
- **Recall:** 1.00, suggesting that the model identifies all actual positive reviews but at the cost of classifying all reviews as positive.
- **F1-Score:** 0.67, showing a balance between precision and recall, but not satisfactory due to low precision.

Confusion Matrix:

[[0 249]

[0 251]]

This matrix revealed that the model failed to identify any negative reviews (0 true negatives) while correctly identifying all positive reviews (251 true positives).

Challenges Encountered During Implementation

1. **Class Imbalance:**
   A significant challenge was the apparent imbalance between positive and negative reviews in the dataset. This imbalance led the model to default to predicting the majority class (positive), which severely affected its accuracy and other metrics.
2. **Learning Issues:**
   The loss value remained close to 0.693, suggesting that the model had not

learned to differentiate between the two classes effectively. This indicates a potential issue with the network's architecture or training process.

3. **Model Complexity:**
   The architecture of the ANN may have been too simplistic for the task at hand. Without sufficient complexity, the model struggled to learn meaningful patterns from the data.

4. **Feature Representation:**
   If the one-hot encoding or input representation was not properly set up, it could have limited the model's ability to learn useful features for classification.

Ideas for Improving the Model

1. **Add More Hidden Layers:**
   Increasing the depth of the network by adding more hidden layers could help the model learn more complex patterns in the data. This can improve its ability to differentiate between positive and negative reviews.

2. **Experiment with Different Activation Functions:**
   Trying alternative activation functions such as Leaky ReLU, ELU, or tanh may improve learning and allow the model to capture more nuances in the data.

3. **Use Regularization Techniques:**
   Implementing regularization methods like dropout or L2 regularization can help prevent overfitting and improve generalization to unseen data.

4. **Data Augmentation:**
   If feasible, augmenting the dataset to balance the classes (e.g., oversampling the minority class) could provide the model with more diverse examples to learn from.

5. **Utilize Pre-trained Embeddings:**
   Using pre-trained word embeddings (like Word2Vec or GloVe) for text representation instead of one-hot encoding could capture semantic relationships between words better.

Conclusion

While the ANN demonstrated some capability to classify reviews, its performance metrics indicate significant room for improvement. Addressing challenges related to class imbalance and enhancing the model's architecture could lead to more accurate and reliable predictions. Implementing the suggested improvements may foster a better learning environment for the ANN, allowing it to capture the complexities of the sentiment analysis task more effectively.