CSC4093 - Programming Assignment 02

Personal Health Mentions Classification Analysis Report

Summary

This report compares the performance between Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (Bi-LSTM) models for classifying tweets into two classes, personal health mentions or non-personal health mentions. The results show that the Bi-LSTM model achieves better performance with 78.78% accuracy compared to 78.11% for the LSTM model, representing a 0.66% higher classification accuracy.

1. Technical Specifications

Model Training Details

- Framework - TensorFlow/Keras
- Optimizer - Adam
- Loss Function - Binary Crossentropy
- Metrics - Accuracy, Precision, Recall, F1-Score

Data Statistics

Total Test Samples	3,331
Non-Personal Health	2,364 (71.0%)
Personal Health	967 (29.0%)
Class Imbalance Ratio	2.44:1

2. Model Architecture and Hyperparameters

Both models were implemented with identical hyperparameters for fair comparison:

Shared Configuration

- Embedding Dimension - 100
- LSTM Output Units - 128
- Batch Size - 128
- Training Epochs - 10
- Dropout Rate - 0.5
- Class Weights - {0: 1.0, 1: 2.5} (to address class imbalance)

3. Performance Comparison

Overall Accuracy Metrics

Model	Correct Predictions	Wrong Predictions	Accuracy (%)
LSTM	2,602	729	78.11%
Bi-LSTM	2,624	707	78.78%

Detailed Classification Reports

LSTM Classification Report

Class	Precision	Recall	F1-Score	Support
Non-Personal Health	0.78	0.97	0.86	2,364
Personal Health	0.83	0.31	0.45	967
Accuracy			0.78	3,331
Macro Average	0.80	0.64	0.66	3,331
Weighted Average	0.79	0.78	0.74	3,331

Bi-LSTM Classification Report

Class	Precision	Recall	F1-Score	Support
Non-Personal Health	0.79	0.96	0.87	2,364
Personal Health	0.81	0.35	0.49	967
Accuracy			0.79	3,331
Macro Average	0.80	0.66	0.68	3,331
Weighted Average	0.79	0.79	0.76	3,331

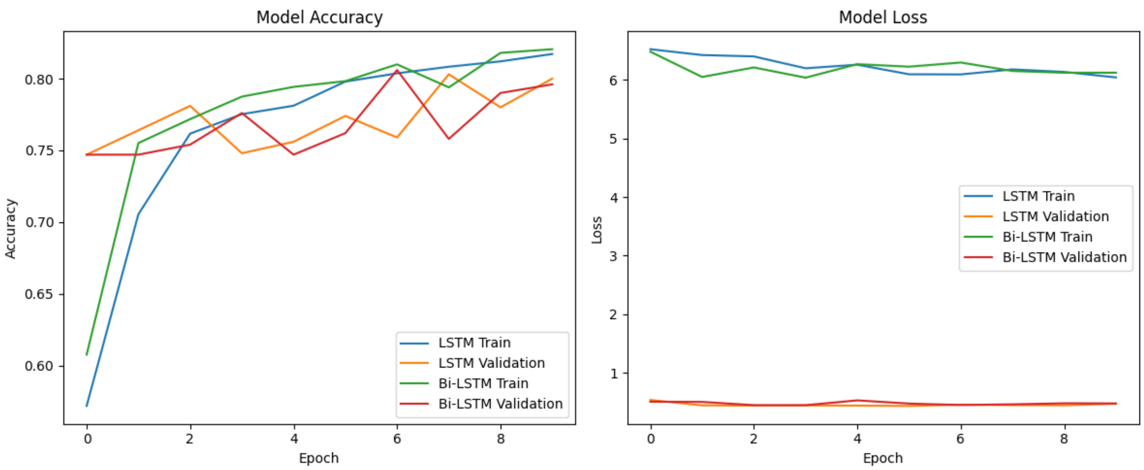

Figure 01: Model Accuracy and Loss Curves: Training and validation performance over 10 epochs

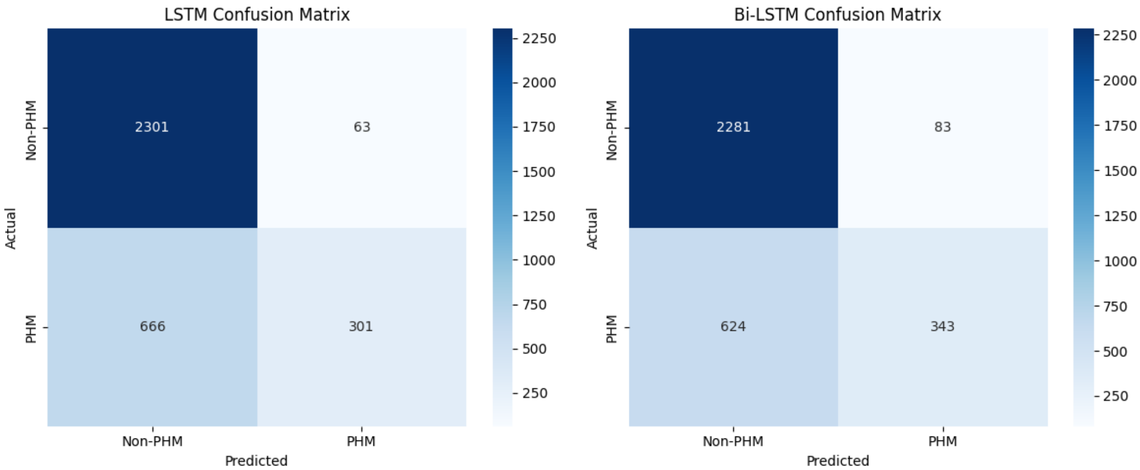

Figure 02: Confusion Matrices: Detailed classification performance for both LSTM and Bi-LSTM models

4. Discussion and Analysis

Why Bi-LSTM Outperforms LSTM

Bidirectional Context Processing

The better performance of the Bi-LSTM model can be due to its ability to process sequential information in both forward and backward directions. This bidirectional processing is beneficial for health mention classification because,

1. Health-related tweets often contain contextual clues both before and after key medical terms
2. Negation Detection require understanding of both forward and backward context
3. Health mentions may reference past, present, or future conditions requiring comprehensive context

Enhanced Feature Extraction

The bidirectional architecture effectively doubles the feature representation capacity by combining,

- Forward LSTM output capturing left-to-right dependencies
- Backward LSTM output capturing right-to-left dependencies
- Combined representation providing richer semantic understanding

Class Imbalance Impact

The dataset exhibits significant class imbalance with 2,364 non-personal health mentions versus 967 personal health mentions.

Due to this class imbalance,

High Recall, Low Precision for Majority Class

Both models achieve high recall (>0.96) for non-personal health mentions, indicating they successfully identify most non-health-related tweets but occasionally misclassify personal health mentions.

Low Recall for Minority Class

The recall for personal health mentions remains low (0.31-0.35) despite class weighting, suggesting the models struggle to identify all health-related content.

Hyperparameter Impact Analysis

Dropout Regularization (0.5)

The high dropout rate of 0.5 helps prevent overfitting, particularly important given,

- Limited training data for the minority class
- Complex bidirectional architecture in Bi-LSTM
- Noisy nature of social media text

Class Weights (0:1, 1:2.5)
The 2.5 weight for personal health mentions tries to address class imbalance by,

- Increasing the penalty for misclassifying health mentions
- Encouraging the model to learn minority class patterns

Embedding Dimension (100)
The 100-dimensional embeddings provide sufficient capacity for capturing health-related semantic relationships.

5. Conclusion

Key Findings

1. Bi-LSTM achieves higher accuracy (78.78% vs 78.11%) demonstrating the value of bidirectional processing for health mention classification

2. Both models identify non-personal health mentions better, but struggle with personal health mentions due to class imbalance

3. The bidirectional architecture provides enhanced contextual understanding, which is valuable for health-related language

Recommendations for Improvement

1. Data Augmentation - Increase training data for personal health mentions through synthetic data generation, and external health dataset integration

2. Advanced Architectures - Consider implementing attention mechanisms, Transformer-based models (BERT, RoBERTa), and ensemble methods

3. Preprocessing Enhancements - Improve text processing through medical entity recognition, specialized health vocabulary expansion, and advanced normalization techniques