m\_Health Dataset Report

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***Objective***

Our project's main goal is to find the best deep learning model for our dataset, mHealth (mobile health). We prioritize three aspects: processing speed, efficiency over time, and accuracy. Our initial focus is to measure how quickly each model processes data and produces results. Following this, we evaluate how well these results match actual observations. This evaluation includes experimenting with various distinct models, each with its own unique approach to understanding the mHealth dataset.

We conducted an exhaustive evaluation of six distinct models: RNN, GRU, LSTM, BiLSTM, CNN+RNN, and CNN+LSTM, across various anatomical regions, specifically Chest, Ankle, and Wrist. Employing a rigorous training and testing approach, we meticulously examined the performance of these models under each configuration. This comprehensive analysis encompassed both intra-region assessments, involving training and testing within the same region (Chest, Ankle, and Wrist), and cross-region analyses. The latter involved training on one region and subsequently testing on another, covering combinations such as Chest-Ankle, Chest-Wrist, Ankle-Chest, Ankle-Wrist, Wrist-Chest, and Wrist-Ankle. This multifaceted experimentation yielded invaluable insights into the models' adaptability and highlighted the crucial role of region-specific learning patterns in ensuring precise predictions.

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***ABOUT THE MODELS***

**1. Recurrent Neural Network (RNN):**

The RNN model was employed to capture sequential patterns and dependencies within the data. This architecture is well-suited for time-series data or sequences where past information influences future predictions. The RNN architecture consists of an input layer, followed by a recurrent layer, and a dense output layer. Despite its ability to capture sequential information, it often suffers from the vanishing gradient problem.

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Layer (type) Output Shape Param #

=================================================================

simple\_rnn (SimpleRNN) (None, 30) 960

dense (Dense) (None, 13) 403

=================================================================

Total params: 1,363

Trainable params: 1,363

Non-trainable params: 0

**2. Gated Recurrent Unit (GRU):**

Similar to the LSTM, the GRU model aims to overcome the vanishing gradient problem of traditional RNNs. It introduces gating mechanisms that control the flow of information through the network, enabling it to capture long-range dependencies more effectively than the standard RNN.

Layer (type) Output Shape Param #

=================================================================

gru (GRU) (None, 4, 30) 2970

gru\_1 (GRU) (None, 30) 5580

dense\_3 (Dense) (None, 13) 403

=================================================================

Total params: 8,953

Trainable params: 8,953

Non-trainable params: 0

**3. Long Short-Term Memory (LSTM):**

LSTM is a variant of RNN that's designed to better capture long-term dependencies in sequential data. It achieves this through its memory cell, input, output, and forget gates. LSTMs have been widely used in various natural language processing tasks and time-series analysis.

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Layer (type) Output Shape Param #

=================================================================

lstm (LSTM) (None, 4, 30) 3840

lstm\_1 (LSTM) (None, 30) 7320

dense\_1 (Dense) (None, 13) 403

=================================================================

Total params: 11,563

Trainable params: 11,563

Non-trainable params: 0

**4. Bidirectional LSTM (BiLSTM):**

The BiLSTM model enhances the LSTM architecture by processing the input sequence in both forward and backward directions. This enables the model to capture contextual information from both past and future contexts, resulting in richer representations.

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Layer (type) Output Shape Param #

=================================================================

bidirectional (Bidirectiona (None, 4, 20) 960

l)

bidirectional\_1 (Bidirection (None, 20) 2480

nal)

dense\_2 (Dense) (None, 13) 273

activation (Activation) (None, 13) 0

=================================================================

Total params: 3,713

Trainable params: 3,713

Non-trainable params: 0

**5. CNN + RNN:**

The combination of CNN and RNN leverages the strengths of both architectures. The CNN extracts spatial features from the data, which are then passed to the RNN for sequential processing. This approach is particularly effective when the data exhibits both spatial and temporal dependencies.

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Layer (type) Output Shape Param #

=================================================================

conv1d (Conv1D) (None, 4, 512) 2048

simple\_rnn\_1 (SimpleRNN) (None, 512) 524800

activation\_1 (Activation) (None, 512) 0

flatten (Flatten) (None, 512) 0

dense\_4 (Dense) (None, 18) 9234

=================================================================

Total params: 536,082

Trainable params: 536,082

Non-trainable params: 0

**6. CNN + LSTM:**

Similar to the previous model, the CNN + LSTM architecture merges the capabilities of CNN and LSTM. The CNN extracts spatial features, and the LSTM processes the sequential aspects of the data. This combination is useful for tasks where both image-based features and temporal dependencies are critical.

Layer (type) Output Shape Param #

=================================================================

conv1d\_1 (Conv1D) (None, 4, 64) 256

lstm\_4 (LSTM) (None, 128) 98816

flatten\_1 (Flatten) (None, 128) 0

dense\_5 (Dense) (None, 18) 2322

=================================================================

Total params: 101,394

Trainable params: 101,394

Non-trainable params: 0

**Optimizer used: Adam || Learning Rate: 0.0001**

1. Training and Testing on Chest

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | RNN | LSTM | BiLSTM | GRU | CNN+  RNN | CNN+  LSTM |
| ***Training:*** |  |  |  |  |  |  |
| Loss  (in %) | 34 | 25 | 27 | 17 | 2 | 8 |
| Accuracy  (in %) | 89 | 93 | 92 | 95 | 99 | 97 |
| Val\_loss  (in %) | 15 | 3 | 4 | 1 | 3 | 9 |
| Val\_accuracy  (in %) | 94 | 99 | 98 | 99 | 100 | 99 |
| Elapsed Time in Seconds | 263.43 | 189.72 | 284.33 | 205.77 | 322.95 | 203.59 |
| ***Testing:*** |  |  |  |  |  |  |
| Loss  (in %) | 15 | 3 | 4 | 1 | 4 | 9 |
| Accuracy  (in %) | 94 | 99 | 99 | 99 | 99 | 99 |
| Avg. Training Loss (in %) | 34 | 25 | 27 | 17 | 2 | 8 |
| Avg Training Accuracy  (in %) | 89 | 93 | 92 | 95 | 99 | 97 |

2. Training and Testing on Ankle

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | RNN | LSTM | BiLSTM | GRU | CNN+  RNN | CNN+  LSTM |
| ***Training:*** |  |  |  |  |  |  |
| Loss (in %) | 39 | 29 | 34 | 22 | 0 | 11 |
| Accuracy  (in %) | 87 | 91 | 89 | 93 | 99 | 96 |
| Val\_loss  (in %) | 16 | 10 | 15 | 5 | 0 | 2 |
| Val\_accuracy  (in %) | 94 | 96 | 93 | 98 | 99 | 99 |
| Elapsed Time in Seconds | 383.04 | 200.49 | 328.28 | 205.02 | 479.44 | 203.86 |
| ***Testing:*** |  |  |  |  |  |  |
| Loss (in %) | 16 | 10 | 15 | 5 | 0 | 2 |
| Accuracy (in %) | 94 | 96 | 93 | 98 | 99 | 99 |
| Avg. Training Loss (in %) | 39 | 29 | 34 | 22 | 0 | 1 |
| Avg Training Accuracy  (in %) | 87 | 91 | 89 | 93 | 99 | 96 |

3. Training and Testing on Wrist

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | RNN | LSTM | BiLSTM | GRU | CNN+  RNN | CNN+  LSTM |
| ***Training:*** |  |  |  |  |  |  |
| Loss (in %) | 42 | 31 | 37 | 21 | 7 | 15 |
| Accuracy  (in %) | 87 | 90 | 88 | 94 | 97 | 95 |
| Val\_loss  (in %) | 19 | 11 | 14 | 3 | 1 | 4 |
| Val\_accuracy  (in %) | 94 | 96 | 95 | 99 | 99 | 98 |
| Elapsed Time in Seconds | 414.06 | 235.81 | 448.63 | 209.87 | 563.25 | 179.25 |
| ***Testing:*** |  |  |  |  |  |  |
| Loss (in %) | 19 | 11 | 14 | 3 | 1 | 4 |
| Accuracy  (in %) | 94 | 96 | 95 | 99 | 99 | 98 |
| Avg. Training Loss (in %) | 42 | 31 | 37 | 21 | 7 | 15 |
| Avg Training Accuracy  (in %) | 87 | 90 | 88 | 94 | 97 | 95 |

4. Training on Chest and Testing on Ankle

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | RNN | LSTM | BiLSTM | GRU | CNN+  RNN | CNN+  LSTM |
| ***Training:*** |  |  |  |  |  |  |
| Loss (in %) | 33 | 25 | 30 | 17 | 2 | 8 |
| Accuracy  (in %) | 90 | 93 | 91 | 95 | 99 | 97 |
| Val\_loss  (in %) | 15 | 3 | 7 | 1 | 2 | 0.01 |
| Val\_accuray  (in %) | 94 | 99 | 97 | 99 | 100 | 99 |
| Elapsed Time in Seconds  (source) | 209.92 | 204.82 | 291.08 | 204.61 | 323.39 | 146.06 |
| Elapsed Time in Seconds  (Target) | 12.18 | 20.52 | 20.52 | 10.28 | 20.52 | 10.29 |
| ***Testing:*** |  |  |  |  |  |  |
| Loss (in %) | 21 | 4 | 9 | 3 | 0.2 | 0.7 |
| Accuracy  (in %) | 93 | 98 | 97 | 99 | 99 | 99 |
|  |  |  |  |  |  |  |
| Avg. Training Loss (in %) | 29 | 5 | 10 | 6 | 0.09 | 1.7 |
| Avg Training Accuracy  (in %) | 91 | 98 | 96 | 98 | 99 | 99 |

5. Training on Chest and Testing on Wrist

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | RNN | LSTM | BiLSTM | GRU | CNN+  RNN | CNN+  LSTM |
| ***Training:*** |  |  |  |  |  |  |
| Loss (in %) | 34 | 26 | 28 | 17 | 2 | 8 |
| Accuracy  (in %) | 90 | 93 | 92 | 95 | 99 | 97 |
| Val\_loss  (in %) | 16 | 4 | 2 | 2 | 3 | 0.01 |
| Val\_accuray  (in %) | 94 | 99 | 99 | 99 | 99 | 99 |
| Elapsed Time in Seconds  (source) | 233.58 | 210.05 | 327.48 | 206.35 | 323.10 | 203.71 |
| Elapsed Time in Seconds  (Target) | 20.53 | 11.69 | 20.57 | 11.12 | 20.52 | 9.99 |
| ***Testing:*** |  |  |  |  |  |  |
| Loss (in %) | 24 | 7 | 10 | 5 | 0.1 | 1 |
| Accuracy  (in %) | 94 | 97 | 96 | 98 | 99 | 99 |
| Avg. Training Loss (in %) | 33 | 12 | 15 | 12 | 0.08 | 3 |
| Avg Training Accuracy  (in %) | 90 | 96 | 94 | 96 | 99 | 99 |

6. Training on Ankle and Testing on Chest

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | RNN | LSTM | BiLSTM | GRU | CNN/RNN | CNN/LSTM |
| ***Training:*** |  |  |  |  |  |  |
| Loss (in %) | 40 | 25 | 32 | 18 | 0.3 | 0.8 |
| Accuracy  (in %) | 87 | 93 | 91 | 95 | 99 | 97 |
| Val\_loss  (in %) | 19 | 5 | 10 | 0.2 | 0.012 | 0.04 |
| Val\_accuracy  (in %) | 93 | 98 | 96 | 99 | 99 | 99 |
| Elapsed Time in Seconds  (source) | 262.95 | 204.85 | 327.59 | 205.79 | 284.70 | 204.30 |
| Elapsed Time in Seconds  (Target) | 11.03 | 11.07 | 20.52 | 20.55 | 20.53 | 10.28 |
| ***Testing:*** |  |  |  |  |  |  |
| Loss (in %) | 24 | 5 | 12 | 0.2 | 0.03 | 0.06 |
| Accuracy  (in %) | 91 | 98 | 96 | 99 | 99 | 99 |
| Avg. Training Loss (in %) | 31 | 63 | 14 | 0.2 | 0.06 | 0.2 |
| Avg Training Accuracy  (in %) | 89 | 98 | 95 | 99 | 99 | 99 |

7. Training on Ankle and Testing on Wrist

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | RNN | LSTM | BiLSTM | GRU | CNN/RNN | CNN/LSTM |
| ***Training:*** |  |  |  |  |  |  |
| Loss (in %) | 36 | 28 | 36 | 20 | 0.4 | 11 |
| Accuracy  (in %) | 88 | 91 | 88 | 94 | 98 | 96 |
| Val\_loss  (in %) | 16 | 11 | 15 | 0.3 | 0.02 | 0.2 |
| Val\_accuracy  (in %) | 94 | 96 | 93 | 98 | 99 | 99 |
| Elapsed Time in Seconds  (source) | 143.33 | 451.49 | 570.86 | 448.46 | 1824.17 | 744.19 |
| Elapsed Time in Seconds  (Target) | 10.32 | 41.05 | 41.03 | 26.39 | 104.93 | 81.98 |
| ***Testing:*** |  |  |  |  |  |  |
| Loss (in %) | 27 | 18 | 25 | 0.5 | 0.2 | 0.6 |
| Accuracy  (in %) | 90 | 94 | 91 | 98 | 99 | 98 |
| Avg. Training Loss (in %) | 33 | 23 | 31 | 0.7 | 0.3 | 0.9 |
| Avg Training Accuracy  (in %) | 88 | 92 | 89 | 98 | 98 | 97 |

8. Training on Wrist and Testing on Chest

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | RNN | LSTM | BiLSTM | GRU | CNN/RNN | CNN/  LSTM |
| ***Training:*** |  |  |  |  |  |  |
| Loss (in %) | 34 | 28 | 32 | 20 | 3 | 9 |
| Accuracy  (in %) | 90 | 91 | 91 | 93 | 99 | 97 |
| Val\_loss  (in %) | 14 | 7 | 4 | 4 | 4 | 0 |
| Val\_accuracy  (in %) | 96 | 97 | 98 | 98 | 100 | 99 |
| Elapsed Time in Seconds  (source) | 262.95 | 264.77 | 320.74 | 166.27 | 322.98 | 203.53 |
| Elapsed Time in Seconds  (Target) | 13.35 | 11.60 | 20.52 | 9.88 | 20.55 | 10.28 |
| ***Testing:*** |  |  |  |  |  |  |
| Loss (in %) | 23 | 10 | 5 | 6 | 0 | 1 |
| Accuracy  (in %) | 94 | 98 | 98 | 98 | 100 | 99 |
| Avg. Training Loss (in %) | 31 | 12 | 74 | 10 | 0 | 2 |
| Avg Training Accuracy  (in %) | 90 | 96 | 98 | 97 | 99 | **99** |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | RNN | LSTM | BiLSTM | GRU | CNN/RNN | CNN/LSTM |
| ***Training:*** |  |  |  |  |  |  |
| Loss (in %) | 40 | 31 | 43 | 22 | 7 | 14 |
| Accuracy  (in %) | 88 | 91 | 86 | 93 | 97 | 95 |
| Val\_loss  (in %) | 18 | 10 | 21 | 5 | 1 | 3 |
| Val\_accuracy  (in %) | 95 | 97 | 93 | 98 | 99 | 99 |
| Elapsed Time in Seconds  (source) | 383.25 | 264.83 | 337.99 | 206.11 | 563.08 | 203.68 |
| Elapsed Time in Seconds  (Target) | 20.56 | 12.64 | 20.53 | 10.35 | 41.01 | 10.28 |
| ***Testing:*** |  |  |  |  |  |  |
| Loss (in %) | 25 | 16 | 25 | 6 | 2 | 7 |
| Accuracy  (in %) | 91 | 94 | 91 | 98 | 99 | 98 |
| Avg. Training Loss (in %) | 29 | 19 | 29 | 8 | 2 | 87 |
| Avg Training Accuracy  (in %) | 89 | 93 | 89 | 97 | 99 | **97** |

9. Training on Wrist and Testing on Ankle

**Conclusion**

From the observations, it can be inferred that certain models perform consistently well across different configurations. For instance, models like CNN+RNN and CNN+LSTM exhibit exceptionally high accuracy and low loss values in most cases. On the other hand, traditional RNN, LSTM, BiLSTM, and GRU models also showcase competitive performance but might have slightly higher losses or lower accuracies compared to the CNN-based models.

Additionally, it's evident that the choice of anatomical region for training and testing can influence the model's performance. Some models demonstrate higher adaptability to specific regions, as indicated by their better performance in intra-region assessments compared to cross-region evaluations.

In terms of processing time, there are variations among the models, with CNN-based models generally exhibiting longer processing times compared to traditional RNN and LSTM models. However, this difference in processing time should be weighed against the models' performance metrics to determine the most suitable choice for the specific application's needs.

In conclusion, the CNN+RNN and CNN+LSTM models appear to consistently excel in accuracy and loss metrics across various training and testing scenarios. Nevertheless, the choice of model should be tailored to the specific anatomical region and processing time constraints of the application. These findings emphasize the importance of understanding the interplay between model performance, anatomical variability, and computational efficiency when selecting a deep learning model for mHealth applications.

**THANK YOU**