

## IMDB Sentiment Classification: RNN vs ANN

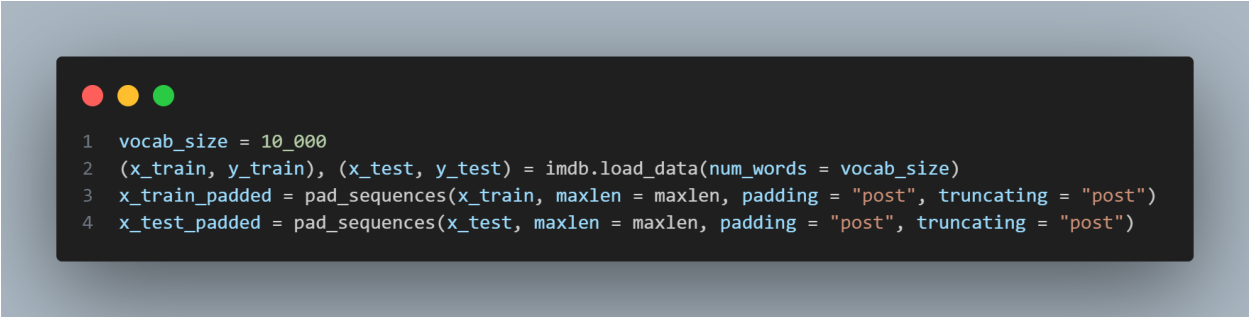
### Objective

To implement and compare two different neural network architectures (RNN and ANN) for binary sentiment classification on the IMDB movie reviews dataset using TensorFlow and Keras.

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### Dataset and Preprocessing

- **Dataset:** IMDB reviews dataset (25,000 training and 25,000 testing samples).
- **Preprocessing:**
  - Used only the top 10,000 most frequent words.
  - Applied padding to ensure uniform input length.
  - Used maxlen = 467 (maximum review length) for padding.



```
1 vocab_size = 10_000
2 (x_train, y_train), (x_test, y_test) = imdb.load_data(num_words = vocab_size)
3 x_train_padded = pad_sequences(x_train, maxlen = maxlen, padding = "post", truncating = "post")
4 x_test_padded = pad_sequences(x_test, maxlen = maxlen, padding = "post", truncating = "post")
```

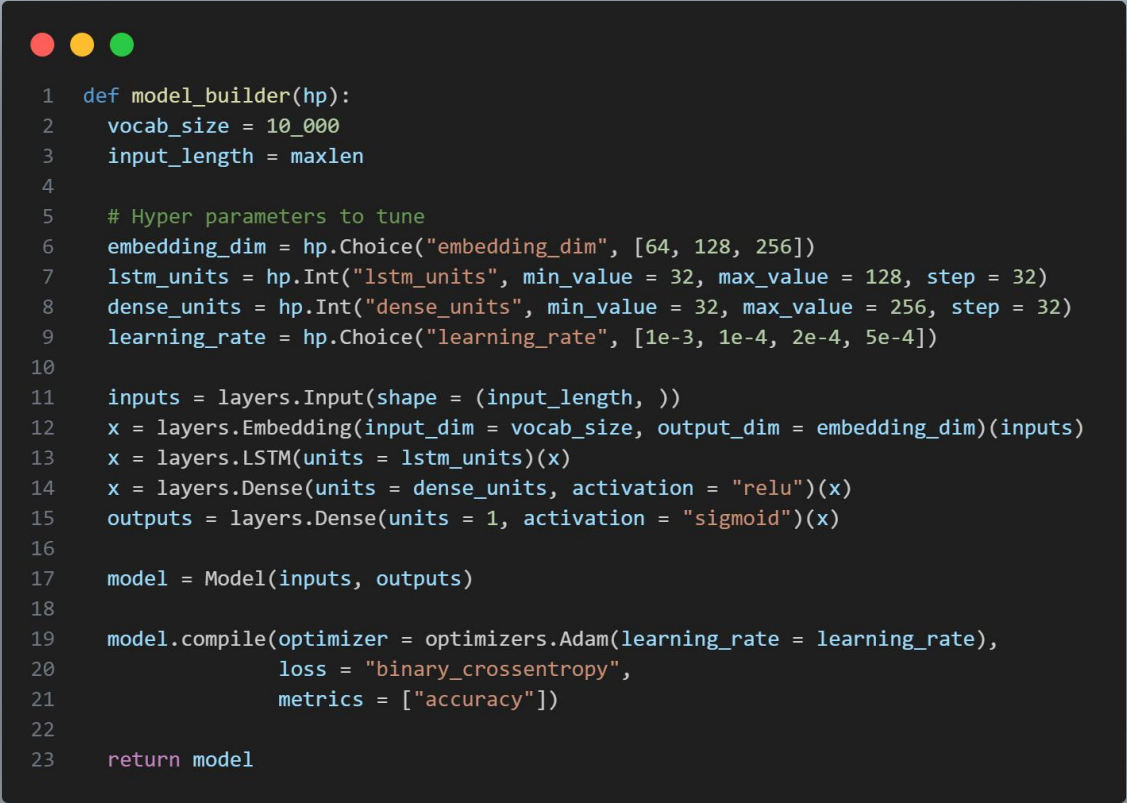
### Model 1: Recurrent Neural Network (RNN)

#### Architecture:

- Embedding Layer
- LSTM Layer
- Dense Layer
- Output Layer

#### Hyperparameter Tuning with Keras Tuner

- Tuned: embedding\_dim, lstm\_units, dense\_units, learning\_rate



```

1  def model_builder(hp):
2      vocab_size = 10_000
3      input_length = maxlen
4
5      # Hyper parameters to tune
6      embedding_dim = hp.Choice("embedding_dim", [64, 128, 256])
7      lstm_units = hp.Int("lstm_units", min_value = 32, max_value = 128, step = 32)
8      dense_units = hp.Int("dense_units", min_value = 32, max_value = 256, step = 32)
9      learning_rate = hp.Choice("learning_rate", [1e-3, 1e-4, 2e-4, 5e-4])
10
11     inputs = layers.Input(shape = (input_length, ))
12     x = layers.Embedding(input_dim = vocab_size, output_dim = embedding_dim)(inputs)
13     x = layers.LSTM(units = lstm_units)(x)
14     x = layers.Dense(units = dense_units, activation = "relu")(x)
15     outputs = layers.Dense(units = 1, activation = "sigmoid")(x)
16
17     model = Model(inputs, outputs)
18
19     model.compile(optimizer = optimizers.Adam(learning_rate = learning_rate),
20                  loss = "binary_crossentropy",
21                  metrics = ["accuracy"])
22
23     return model

```

### Training:

- Used early stopping
- Trained on 80% of training data, validated on 20%

### Performance:

- Validation Accuracy: ~87%
- Observed some overfitting (validation loss increased mid-training)

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## Model 2: Artificial Neural Network (ANN)

### Architecture:

- Embedding Layer
- GlobalAveragePooling1D

- Dense Layer
- Output Layer

```
1 def create_ann_model(vocab_size = 10_000, input_length = maxlen):
2
3     model = Sequential([
4         Input(shape = (input_length,)),
5         Embedding(input_dim = vocab_size, output_dim = 128),
6         GlobalAveragePooling1D(),
7         Dense(64, activation = "relu"),
8         Dropout(0.3),
9         Dense(1, activation = "sigmoid")
10    ])
11
12    model.compile(
13        loss = "binary_crossentropy",
14        optimizer = optimizers.Adam(learning_rate = 0.001),
15        metrics = ["accuracy"]
16    )
17    return model
```

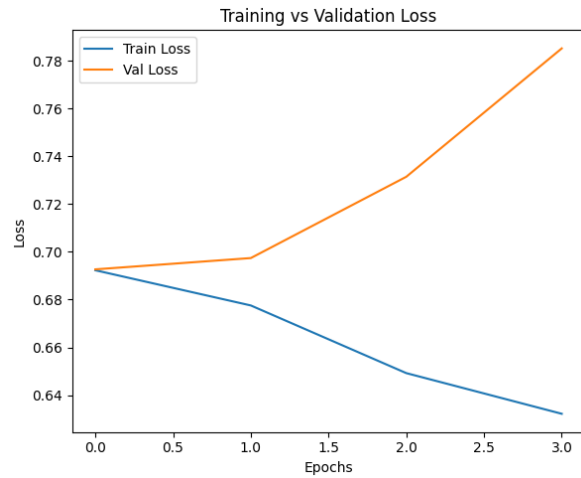
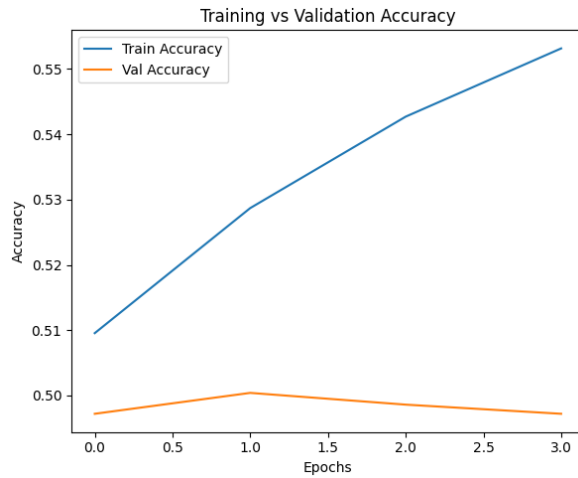
#### Performance:

- Validation Accuracy: ~89%
- Validation loss decreased smoothly — indicating better generalization

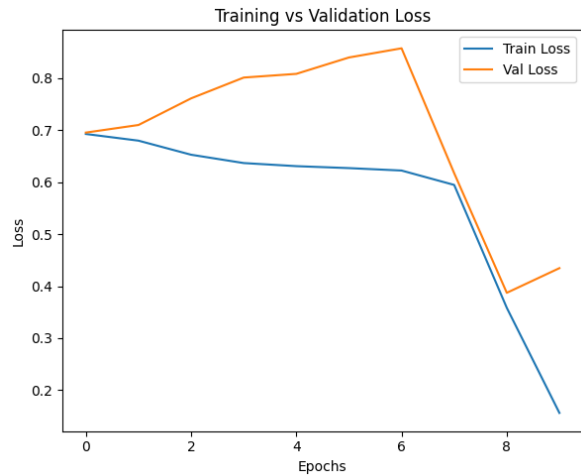
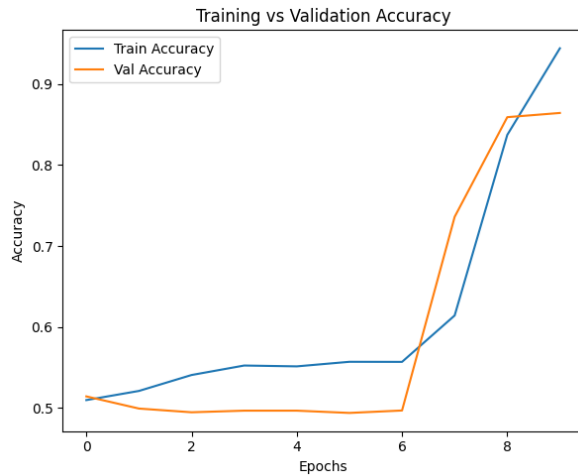
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#### Metrics Visualization:

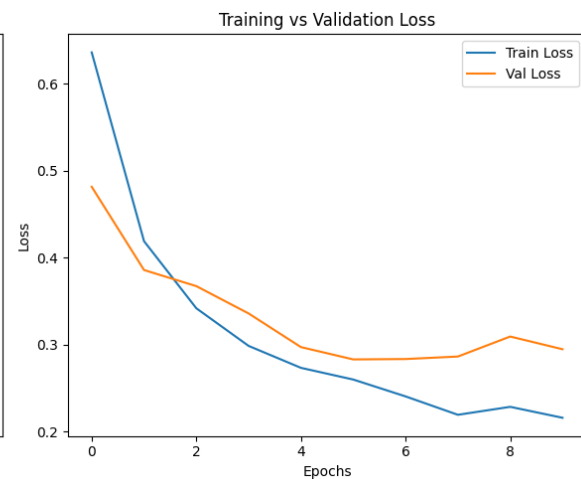
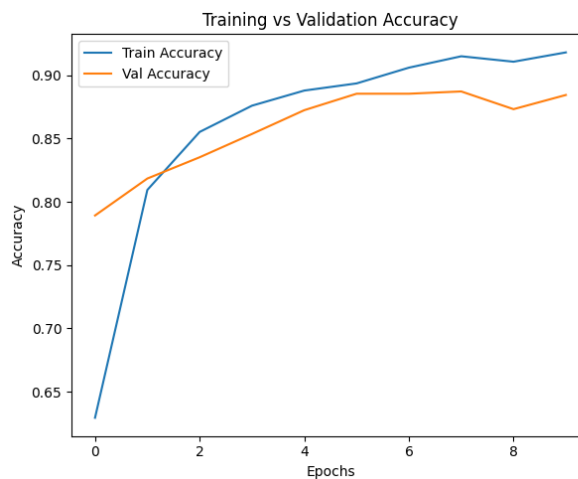
## Base Model's Visualization



## Fined-tuned model Visualization



## ANN model Visualization



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## Model Comparison

Metric	RNN Model	ANN Model
Validation Accuracy	~87%	~89%
Training Speed	Slower	Faster
Generalization	Moderate	Strong

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## Analysis & Insights

- Despite being simpler, the ANN model outperformed the RNN.
  - The IMDB dataset is relatively small and binary-labeled — sequence information might not be essential.
  - RNNs are powerful but sensitive to overfitting and hyperparameter tuning.
  - For basic sentiment classification tasks, FFNNs can be surprisingly strong baselines.
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## Conclusion

- RNNs may not always be the best choice for all NLP tasks, especially when the dataset is small and task is simple.
- ANN provided better generalization and stability with faster training.
- Hyperparameter tuning, early stopping, and model simplicity play a significant role in practical performance.

This exercise provided practical insight into model selection, tuning, and the importance of testing assumptions even in deep learning.