

# Model Optimization and Tuning Phase Template

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Team ID	SWTID1726832093
Project Title	Analysis of Amazon Cell Phone Reviews Using NLP Technique
Maximum Marks	10 Marks

## Model Optimization and Tuning Phase

The Model Optimization and Tuning Phase involves refining neural network models for peak performance. It includes optimized model code, fine-tuning hyperparameters, comparing performance metrics, and justifying the final model selection for enhanced predictive accuracy and efficiency.

### Hyperparameter Tuning Documentation (8 Marks):

Model	Tuned Hyperparameters
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## CNN

- **Learning Rate:** 0.0001 (Controls the step size during optimization)
- **Batch Size:** 64 (Number of samples processed before the model is updated)
- **Dropout Rate:** 0.5 (Rate of dropout for regularization)
- **Kernel Size (3, 3):** The dimensions of the filter used in the convolution layer. Smaller kernels capture fine details, while larger kernels capture broader features.
- **Pooling Size (2, 2):** The size of the pooling window in the max pooling layer, which reduces the dimensionality of the data and helps to retain the most important features.
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[ ] ANALYSIS OF AMAZON CELL PHONE BY USING NLP



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# CNN Model Code

```
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

# Parameters
image_height, image_width, channels = 100, 100, 3 # Image dimensions

model2 = Sequential()
model2.add(Conv2D(128, kernel_size=(3, 3), activation='relu', input_shape=(image_height, image_width, channels)))
model2.add(MaxPooling2D(pool_size=(2, 2)))
model2.add(Dropout(0.3))
model2.add(Flatten())
model2.add(Dense(1, activation='sigmoid'))

model2.compile(optimizer=keras.optimizers.Adam(), loss='binary_crossentropy', metrics=['accuracy'])
```

<p><b><u>Bidirectional</u></b></p> <p><b><u>LSTM</u></b></p>	<ul style="list-style-type: none"><li>● <b>Dropout Rate (0.5):</b> The fraction of neurons to drop during training to prevent overfitting. A higher dropout rate can help the model generalize better by avoiding reliance on specific neurons.</li><li>● <b>Number of Epochs (50):</b> The number of complete passes through the training data. More epochs can lead to better learning, but excessive epochs may cause overfitting.</li><li>● <b>Hidden Units (100, 50):</b> The number of neurons in the LSTM layers. More hidden units can capture more complex patterns but may also increase the risk of overfitting.</li></ul> <div><div>+ Code + Text All changes saved</div><div>Double-click (or enter) to edit</div><div><div>{x}</div><div>Generate</div><div>ANALYSIS OF AMAZON CELL PHONE BY USING NLP</div></div><div><div>3s</div><div><pre># Bidirectional LSTM Model Code import keras from keras.models import Sequential from keras.layers import LSTM, Dense, Dropout, Embedding, Bidirectional  # Parameters vocab_size = 5000 # Vocabulary size embedding_dim = 100 # Dimensionality of the embedding layer max_length = 100 # Maximum length of input sequences  model1 = Sequential() model1.add(Embedding(input_dim=vocab_size, output_dim=embedding_dim, input_length=max_length)) model1.add(Bidirectional(LSTM(100, return_sequences=True))) model1.add(Dropout(0.5)) model1.add(LSTM(50)) model1.add(Dense(1, activation='sigmoid'))  model1.compile(optimizer=keras.optimizers.Adam(learning_rate=0.0001), loss='binary_crossentropy', metrics=['acc'])</pre></div></div></div>
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**Final Model Selection Justification (2 Marks):**

Final Model	Reasoning
Model 1 (Bidirectional LSTM)	<p>Model 1, which utilizes a Bidirectional Long Short-Term Memory (LSTM) architecture, was chosen as the final optimized model for the analysis of Amazon cell phone reviews due to its ability to effectively capture the sequential dependencies inherent in natural language data.</p> <ul style="list-style-type: none"><li>● <b>Contextual Understanding:</b> The Bidirectional LSTM processes input sequences in both forward and backward directions. This feature allows the model to understand context more comprehensively, which is crucial for sentiment analysis where the meaning of a word can change based on its surrounding words.</li><li>● <b>Handling Long Sequences:</b> LSTMs are particularly adept at managing long-range dependencies, making them suitable for analyzing lengthy reviews. This capability ensures that important information from the beginning of a review is not forgotten as the model processes the entire sequence.</li><li>● <b>Performance Metrics:</b> During validation, Model 1 demonstrated superior performance metrics compared to alternative models, particularly in accuracy, precision, and recall. The F1-score, which balances precision and recall, was notably higher, indicating better overall classification of sentiments.</li><li>● <b>Reduced Overfitting:</b> The hyperparameter tuning, particularly the use of dropout (set to 0.5), effectively mitigated overfitting, allowing the model to generalize well on unseen data. This balance is critical in ensuring the model's reliability in a real-world application.</li></ul>