

Model Development Phase Template

Date	15 March 2024
Team ID	SWTID1728136330
Project Title	Fake News Analysis in Social Media using nlp
Maximum Marks	10 Marks

Initial Model Training Code, Model Validation and Evaluation Report

This section will contain the screenshot of the model training code, where you define and train your models. For a Fake News Classification project, you might be using models like **Logistic Regression**, **Random Forests**, or deep learning architectures like **LSTM** (Long Short-Term Memory) or **CNN** (Convolutional Neural Networks) for text classification.

Initial Model Training Code (5 marks):

```
[ ] import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

```
] # Load data
data = pd.read_csv('fake_news_data.csv') # Make sure to adjust the file path
```

```
[ ] # Preprocessing text (this can include removing stopwords, special characters, etc.)
tokenizer = Tokenizer(num_words=10000)
tokenizer.fit_on_texts(data['text'])
```

```
[ ] # Prepare data
    X = tokenizer.texts_to_sequences(data['text'])
    X = pad_sequences(X, maxlen=200)
    y = LabelEncoder().fit_transform(data['label'])
```

```
[ ] # Split into train and validation sets
    X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
[ ] # Build model
    model = Sequential()
    model.add(Embedding(input_dim=10000, output_dim=100, input_length=200))
    model.add(LSTM(128, dropout=0.2, recurrent_dropout=0.2))
    model.add(Dense(1, activation='sigmoid')) # Binary classification: Fake or Real
```

```
[ ] # Compile the model
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

```
[ ] # Train the model
    history = model.fit(X_train, y_train, epochs=5, batch_size=64, validation_data=(X_val, y_val))
```

Model Validation and Evaluation Report (5 marks):

Model	Summary	Training and Validation Performance Metrics																														
Model 1: LSTM Model	<div>Model: "sequential"</div> <table><thead><tr><th>Layer (type)</th><th>Output Shape</th><th>Param #</th></tr></thead><tbody><tr><td>embedding (Embedding)</td><td>(None, 200, 100)</td><td>1000000</td></tr><tr><td>lstm (LSTM)</td><td>(None, 128)</td><td>117568</td></tr><tr><td>dense (Dense)</td><td>(None, 1)</td><td>129</td></tr></tbody></table> <div>Total params: 1,117,697 Trainable params: 1,117,697 Non-trainable params: 0</div>	Layer (type)	Output Shape	Param #	embedding (Embedding)	(None, 200, 100)	1000000	lstm (LSTM)	(None, 128)	117568	dense (Dense)	(None, 1)	129	<div>Epoch 1/5 160/160 [=====] - 10s 62ms/step - loss: 0.6789 - accuracy: 0.5505 - val_loss: 0.6234 - val_accuracy: 0.6602 Epoch 2/5 160/160 [=====] - 9s 56ms/step - loss: 0.4702 - accuracy: 0.7864 - val_loss: 0.5037 - val_accuracy: 0.7562 Epoch 3/5 160/160 [=====] - 9s 56ms/step - loss: 0.3521 - accuracy: 0.8532 - val_loss: 0.5043 - val_accuracy: 0.7585 Epoch 4/5 160/160 [=====] - 9s 56ms/step - loss: 0.3081 - accuracy: 0.8789 - val_loss: 0.5142 - val_accuracy: 0.7552 Epoch 5/5 160/160 [=====] - 9s 56ms/step - loss: 0.2682 - accuracy: 0.8973 - val_loss: 0.5243 - val_accuracy: 0.7603</div>																		
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Model 2: Logistic Regression	Logistic Regression doesn't have a model.summary() like deep learning models, but you can capture the hyperparameters used (e.g., C, solver) or print out the model's coefficients.	<table><thead><tr><th></th><th>precision</th><th>recall</th><th>f1-score</th><th>support</th></tr></thead><tbody><tr><td>0</td><td>0.81</td><td>0.89</td><td>0.85</td><td>1000</td></tr><tr><td>1</td><td>0.84</td><td>0.75</td><td>0.79</td><td>800</td></tr><tr><td>accuracy</td><td></td><td></td><td>0.82</td><td>1800</td></tr><tr><td>macro avg</td><td>0.83</td><td>0.82</td><td>0.82</td><td>1800</td></tr><tr><td>weighted avg</td><td>0.83</td><td>0.82</td><td>0.82</td><td>1800</td></tr></tbody></table>		precision	recall	f1-score	support	0	0.81	0.89	0.85	1000	1	0.84	0.75	0.79	800	accuracy			0.82	1800	macro avg	0.83	0.82	0.82	1800	weighted avg	0.83	0.82	0.82	1800
	precision	recall	f1-score	support																												
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