



# **Mental Health Chatbot Using Natural Language Processing (NLP)**

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## 1. ABSTRACT:

This project explores the construction of a classification-based mental health chatbot using advanced Natural Language Processing (NLP) and deep learning techniques. Rather than generating free-form responses, the chatbot is designed to select the most appropriate reply from a predefined set of responses based on user inputs. Utilizing Long Short-Term Memory (LSTM) networks, Keras tokenization, and pretrained Word2Vec embeddings, the system demonstrates the multiclassification capability of deep learning models in natural language tasks. The project includes comprehensive data preprocessing, exploratory data analysis (EDA) to handle class imbalance, and performance evaluation to ensure robust classification results. This work highlights the power of combining pretrained semantic representations with sequential neural networks to create reliable and empathetic conversational agents, especially in sensitive domains like mental health support.

**KEYWORDS:** Mental Health, Chatbot, Natural Language Processing, Sentiment Analysis, Intent Recognition, Emotional Support.

## 2. INTRODUCTION:

Artificial Intelligence (AI) and Natural Language Processing (NLP) are revolutionizing the way machines interact with humans, opening new avenues for creating intelligent conversational agents. This project delves into developing a sophisticated mental health chatbot that leverages the capabilities of deep learning for multiclass text classification.

Unlike generative dialogue systems that create responses word-by-word, the focus of this project is on classification-based response selection. The chatbot does not generate new sentences; instead, it intelligently chooses the best predefined response class that aligns with the user's input. This approach offers greater control, safety, and reliability critical factors when dealing with sensitive subjects like emotional distress and mental well-being.

The backbone of this system is a Long Short-Term Memory (LSTM) neural network, chosen for its proven ability to handle sequential data and retain contextual information across long dependencies. The model benefits further from semantic richness by integrating pretrained Word2Vec embeddings, which capture the meanings of words based on their usage in large corpora.

**The objectives of the project are:**

- To build a natural language understanding model capable of accurately classifying user inputs into intent categories.
- To implement thorough data preprocessing techniques including tokenization, sequence padding, and semantic embedding.
- To address dataset imbalance through exploratory data analysis (EDA) and augmentation methods.
- To develop and train an LSTM-based classifier for multiclass response selection.

- To evaluate the model's performance using appropriate metrics and visualize learning trends during training.
- To create a deployable, scalable chatbot system that can provide empathetic, safe, and immediate support to users.

Through this project, we aim to demonstrate how combining pretrained word vectors with deep learning architectures can lead to powerful conversational agents that are contextually aware and emotionally intelligent.

### 3. RELATED WORK:

Various mental health Chat Bots have been developed to offer psychological support. Applications like Woebot and Wysa utilize cognitive behavioral therapy (CBT) principles to help users track their emotions, provide structured interventions, and suggest self-care techniques. However, these systems are typically rule-based, limiting their adaptability and ability to understand complex, nuanced inputs. Our system builds on these approaches by integrating advanced NLP techniques such as contextual embeddings, machine learning for intent classification, and pre-trained transformers for sentiment analysis. This makes the Chat Bot more dynamic and conversational

### 4. BUSINESS UNDERSTANDING:

The primary business objectives of developing this chatbot are:

- **Accessibility:** Provide mental health support 24/7 to users from anywhere in the world.
- **Affordability:** Reduce the cost barrier of mental health care by offering free or low-cost AI-powered support.
- **Early Detection:** Identify early signs of mental health issues through conversational interactions and direct users to appropriate help.
- **User Engagement:** Create a supportive digital environment where users feel heard and understood.

### 5. METHODOLOGY:

#### 5.1 Data Collection:

We used open-source datasets that include emotionally annotated dialogues and mental health-related discussions. These datasets include:

Emotion Dataset (Kaggle): Contains text data labeled with emotional categories such as happy, sad, angry, etc.

The chatbot dataset is carefully organized into three main components: **tag**, **patterns**, and **responses**. This structured format is critical for training the chatbot to understand user inputs correctly and provide appropriate replies.

### 5.1.1 Tag

The **tag** serves as a **label** that defines the **intent** or **category** associated with a particular user input.

- Every user utterance is linked to one specific tag, which represents the overall purpose or meaning behind the input.
- Tags are **abstract identifiers** such as "greeting", "goodbye", "weather", "mental\_health", or "anxiety\_help".
- During model training, the goal is to classify a user's message into the correct tag based on the textual content.
- The tag helps the chatbot decide **what kind of response** is appropriate without having to generate it from scratch.
- **Example:**  
If the user says "Hi there," the model should classify it under the tag "greeting".

### 5.1.2 Patterns

The **patterns** are a **list of example user inputs** or **phrases** that express the meaning or intent captured by the corresponding tag.

- Patterns act as **training examples** that show different ways users might communicate the same intent.
- They help the model learn the variety and diversity of natural language expressions linked to a specific category.
- Patterns are critical for **training** because real-world users will use many different words, tones, and sentence structures to express the same idea.
- In practice, **the more diverse the patterns are**, the better the model can generalize to new, unseen user inputs.
- **Example:**  
For the tag "greeting", possible patterns could be: ["Hi", "Hello", "Hey there", "Good morning", "What's up?"]

### 5.1.3 Responses

The **responses** are a **list of possible bot replies** that the chatbot can use once it identifies the user's intent.

- After the model classifies the user input into a tag, it selects a suitable response from the response list associated with that tag.
- Multiple responses for the same tag add **variety** to the chatbot's interaction, making conversations feel more natural and less repetitive.
- Responses are often **randomly picked** or **contextually selected** to match the situation better.
- **Example:**  
For the tag "greeting", possible bot responses could include: ["Hello!", "Hi there!", "Greetings!", "Nice to meet you!", "Hey, how are you?"]

In our chatbot project, one of the critical challenges identified during data analysis was severe class imbalance. Specifically, we observed that the ratio between the most represented tag (intent) and the least represented tag was approximately 12:1. This means that for every 12 samples belonging to the majority class, there is only 1 sample in the minority class. Such an imbalance is highly detrimental to machine learning models, particularly in classification tasks. It biases the model towards overfitting on the majority classes while neglecting the minority classes. Consequently, the model learns to classify well when the input matches the dominant patterns but fails when encountering underrepresented or rare classes.

[illegible]

To address this challenge, we adopted an automated data augmentation strategy using the Pegasus paraphraser model from the Transformers library. This method ensures that every intent/tag in our dataset has a sufficient number of diverse patterns, enhancing the model’s ability to generalize across variations in user input. Pegasus (Pre-training with Extracted Gap-sentences for Abstractive Summarization) is a transformer-based model originally designed for text summarization

- **State-of-the-art paraphrasing ability:** Pegasus generates high-quality, fluent paraphrases that retain the original meaning while changing surface forms.
- **Contextual rephrasing:** Instead of simply swapping synonyms, Pegasus understands the entire sentence structure and context.

- **Pretrained on diverse datasets:** It can handle both formal and informal sentences, making it suitable for varied user inputs seen in chatbots.
- **Multiple paraphrases per input:** Pegasus can generate several alternative rewrites from a single input pattern.

Thus, Pegasus was an ideal choice to **expand minority class examples** without losing semantic consistency.

### Approach:

The strategy to balance the dataset involved the following theoretical steps:

1. **Pattern Extraction:**  
For each intent/tag in the original dataset, all associated user input patterns were extracted.
2. **Target Setting:**  
A target of **at least 12 patterns** per tag was set. Tags with fewer than 12 patterns needed augmentation.
3. **Paraphrase Generation:**  
Each original pattern was input into the Pegasus paraphraser model, which generated multiple paraphrased versions per pattern. These new patterns preserved the semantic meaning but differed syntactically and lexically.
4. **Pattern Validation:**  
To ensure quality:
  - Newly generated paraphrases were checked to avoid near-duplicates (e.g., only changes in capitalization or punctuation).
  - Only **semantically meaningful** and **unique** paraphrases were retained.
5. **Progressive Augmentation:**  
Newly generated paraphrases were also paraphrased again if needed, until the desired number of patterns (12 per tag) was reached.
6. **Dataset Update:**  
After augmentation, the dataset was updated so that each intent now had an approximately equal number of patterns. The updated dataset was then ready for model training, validation, and testing.

This is a perfect result compared to the original data distribution.



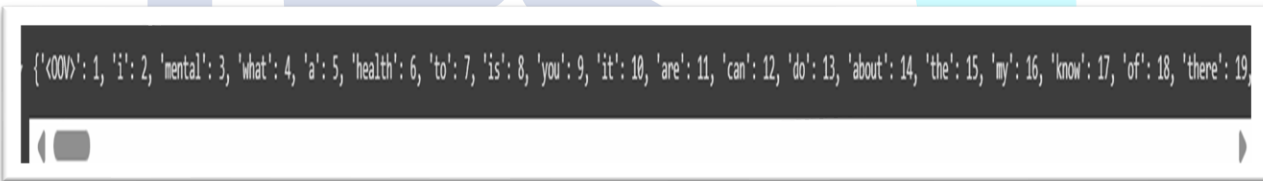


## 6. MODELLING

In the process of preparing textual data for training a deep learning model, several important steps are necessary to ensure that the data is in a format the model can effectively learn from. Three such crucial preprocessing steps are **tokenization**, **padding**, and **label encoding**.

### 6.1 Tokenization:

Tokenization is the process of converting raw text into sequences of numerical tokens that a model can understand. Each word or meaningful sub-word is mapped to a unique integer ID. In our chatbot project, we employ tokenization using a special setting: `oov_token = '<OOV>'`, where "OOV" stands for "out of vocabulary." This mechanism handles rare or unknown words that the tokenizer has not seen during the training phase. When such a word appears in user input, instead of causing an error or being ignored, it is replaced with the special `<OOV>` token. This ensures that the model has a consistent, learnable embedding vector for unknown words, preventing unpredictable behaviour when new or misspelled words are encountered. Additionally, in our model, the embedding layer is set with `trainable=False`, meaning that during training, the pretrained word embeddings (such as Word2Vec vectors) remain fixed. The model cannot modify these embeddings; it can only learn higher-level patterns based on them. This strategy stabilizes training and allows the model to benefit from semantic knowledge captured in the pretrained vectors.



```
{'<OOV>': 1, 'i': 2, 'mental': 3, 'what': 4, 'a': 5, 'health': 6, 'to': 7, 'is': 8, 'you': 9, 'it': 10, 'are': 11, 'can': 12, 'do': 13, 'about': 14, 'the': 15, 'my': 16, 'know': 17, 'of': 18, 'there': 19}
```

### 6.2 Padding:

Padding is another essential step after tokenization because deep learning models, especially LSTMs, require inputs of uniform length. However, in natural conversations, sentences vary widely in length some may be short greetings, while others are long expressions of feelings. To handle this variability, we use the `pad_sequences` method to standardize input lengths. Padding involves adding zeros to the shorter sequences so that every input sequence matches the length of the longest one or a predefined maximum length. This operation ensures that the model processes batches efficiently and maintains structural consistency during learning.

```
x shape : (898, 18)
y shape : (898, 80)
```

### 6.3. Label encoding:

Label encoding is the final important step before model training. Neural networks cannot directly learn from textual labels like "anxiety" or "stress" because they require numerical input. Therefore, we use a Label Encoder to convert categorical intent tags into integer codes. Each unique intent is assigned a distinct integer. For example, the tag "Anxiety" might be mapped to 0, "Stress" to 1, and "Depression" to 2. This numerical representation allows the classification model to output probability distributions over integer classes, which are then mapped back to their corresponding textual intents during prediction. Without label encoding, the model would not be able to perform multi-class classification tasks, which are essential for selecting the correct chatbot response based on user input.

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50,
        51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67,
        68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79])
```

### 6.4. Importing Pre-trained Word2Vec Model

In order to enhance the chatbot's ability to understand natural language semantics, we imported a pre-trained Word2Vec model (GoogleNews-vectors-negative300.bin). Word2Vec transforms individual words into dense vector representations in a high-dimensional space, where words with similar meanings are located close to each other. Instead of learning word embeddings from scratch, we use these pre-trained vectors to provide the model with rich semantic knowledge immediately. This allows the chatbot to recognize variations in user input more effectively; for instance, even if a user uses synonyms or less common phrasing, the model can infer that the underlying intent remains similar. Word2Vec thus acts as a foundation for semantic grounding, improving the model's understanding and generalization across diverse input patterns.

### 6.5. Constructed Embedding Matrix Aligned with Tokenizer Vocabulary

After loading the Word2Vec model, we constructed an embedding matrix to align the Word2Vec vectors with the indices produced by the tokenizer. Every word token generated during tokenization corresponds to a specific row in the embedding matrix. If the token exists in the Word2Vec model, its pre-trained vector is assigned to the respective row. If the token is absent (for example, due to spelling errors, rare words, or newly created tokens), the row is filled with random small values or zeros. This process ensures that every token, whether frequent or rare, has

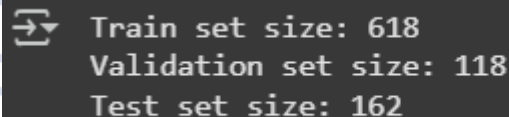
a corresponding numerical representation. The embedding matrix is then used to initialize the model's embedding layer, providing a seamless connection between text and deep learning computations.

## 6.6. Converted Input Patterns to Padded Sequences

Since natural language sentences vary in length, it is crucial to standardize the size of the input sequences before feeding them into an LSTM network. To achieve this, we converted all tokenized input patterns into padded sequences. Shorter sequences are appended with zeros at the end to match the length of the longest sequence or a predefined maximum length. Padding ensures that all inputs within a batch have uniform dimensions, which is essential for efficient batch processing and maintaining compatibility with LSTM architecture. Without padding, the model would struggle with inconsistent input sizes and training would be inefficient or error-prone.

## 6.7. Train-Test Split

To properly evaluate the model's generalization ability, we divided the dataset into two subsets: training and testing. Typically, 80% of the samples are allocated for training, and the remaining 20% are reserved for testing. The training set is used to teach the model the relationship between input patterns and their corresponding intent tags. Meanwhile, the testing set contains patterns that the model has never seen before, allowing for an unbiased assessment of performance. A proper train-test split ensures that the chatbot does not simply memorize the training data but learns meaningful patterns that it can apply to new, unseen user inputs in real-world scenarios.



```
→ Train set size: 618
   Validation set size: 118
   Test set size: 162
```

## 6.8. LSTM Neural Network Model

Long Short-Term Memory (LSTM) networks are a special type of Recurrent Neural Network (RNN) that are particularly well-suited for processing sequential data, such as text. In a typical RNN, information can suffer from short-term memory issues, where earlier words in a sentence lose influence as more words are processed. LSTMs solve this by introducing memory cells and gating mechanisms, which allow them to retain important information across long sequences. In the context of a chatbot, using an LSTM enables the model not only to recognize individual words but also to understand their order and context within the sentence. This sequential understanding is crucial because the meaning of a user's input often depends on how words are related to each other, not just on their isolated meanings. For example, the sentences "I am feeling sad today" and "Today, I am feeling sad" convey the same emotion despite word order differences, and LSTMs are designed to handle such variations effectively.

## 6.9. Embedding Layer Initialized with Word2Vec Matrix

The embedding layer in our model serves as the first hidden layer that transforms tokenized input (integer sequences) into dense vector representations. Instead of training this embedding layer from scratch, we initialize it with the pre-trained Word2Vec embedding matrix. This approach leverages the semantic knowledge captured in Word2Vec, where words with similar meanings already have similar vectors. By initializing the embedding layer with these pretrained vectors, the model starts training with a strong semantic foundation, enabling faster convergence and better language understanding. Additionally, because the embedding layer is set as non-trainable (`trainable=False`), it preserves the original semantic relationships learned from large-scale corpora like Google News, preventing degradation of the quality of word embeddings during model training.

## 6.10. Dense Layers with Softmax Activation for Multi-Class Classification

After processing the input sequence through the LSTM layers, the extracted features are passed to one or more dense layers. Dense layers are fully connected neural layers where every neuron receives input from all neurons in the previous layer. These layers allow the model to learn complex, non-linear patterns in the data, helping it map the extracted sequence features to specific intents. The final output layer is a dense layer that uses a **Softmax activation function**, which is specifically designed for multi-class classification tasks. Softmax transforms the output into a probability distribution across all possible intent classes, ensuring that the sum of the probabilities equals one. The model then selects the class with the highest probability as the predicted intent, allowing the chatbot to choose the most appropriate response for the user's input.

## 7. EVALUATION

### 1. Evaluation with Accuracy and Loss Metrics

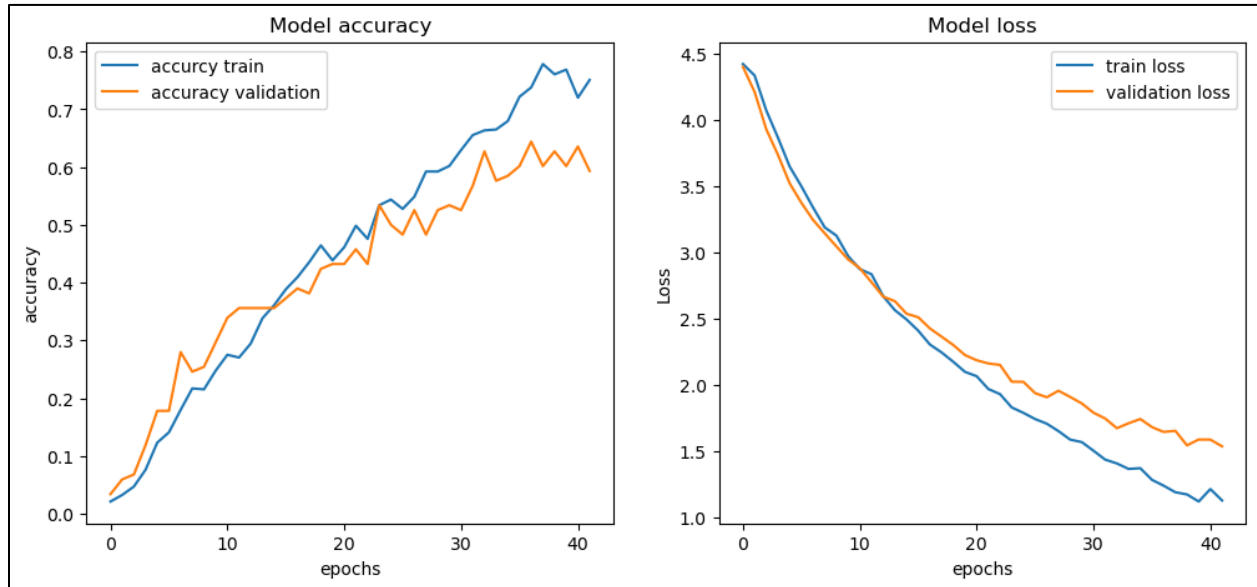
After the chatbot model was trained on the training data, its performance was assessed using unseen test data to measure how well it generalized. Two fundamental evaluation metrics were used: **accuracy** and **loss**.

**Accuracy** measures the percentage of correct predictions out of all predictions made by the model. A higher accuracy indicates that the model is correctly classifying the user's input into the right intent category more frequently. In this case, the model's test accuracy improved steadily during training and reached competitive levels by the end of 40 epochs, suggesting that the model learned meaningful patterns from the data.

**Loss**, on the other hand, quantifies the difference between the predicted outputs and the actual true labels. Lower loss values imply that the model's predicted probability distributions are close to the true labels. Initially, loss was quite high (around 4.5) but decreased consistently across epochs for both training and validation sets. By the end of training, the loss values dropped significantly, indicating effective learning.

Evaluating both accuracy and loss is critical because a model with high accuracy but high loss could still be overconfident or unstable in its predictions. In this chatbot project, the steady

decrease in loss and corresponding increase in accuracy confirmed that the model was learning correctly and becoming more reliable.



**Fig No 3 Model Accuracy and Loss**

## 2. Visualization of Training and Validation Curves

To further understand how the model's learning progressed over time, **training and validation curves** were plotted for both accuracy and loss across the 40 training epochs.

In the **accuracy curve**, both training accuracy and validation accuracy showed a rising trend. Although the training accuracy slightly outperformed the validation accuracy (as expected), the gap between them remained relatively stable without diverging significantly. This indicates that the model was not severely overfitting to the training data — it was able to generalize well to unseen validation examples too.

In the **loss curve**, both training loss and validation loss consistently declined over epochs. There was no sudden increase in validation loss, which would have indicated overfitting. Instead, both curves followed similar trends, suggesting smooth and healthy model learning.

## 3. Confusion Matrix Analysis

Finally, a **confusion matrix** was generated for the testing set, offering a deeper insight into how the model performed across individual intent classes.

In the confusion matrix:

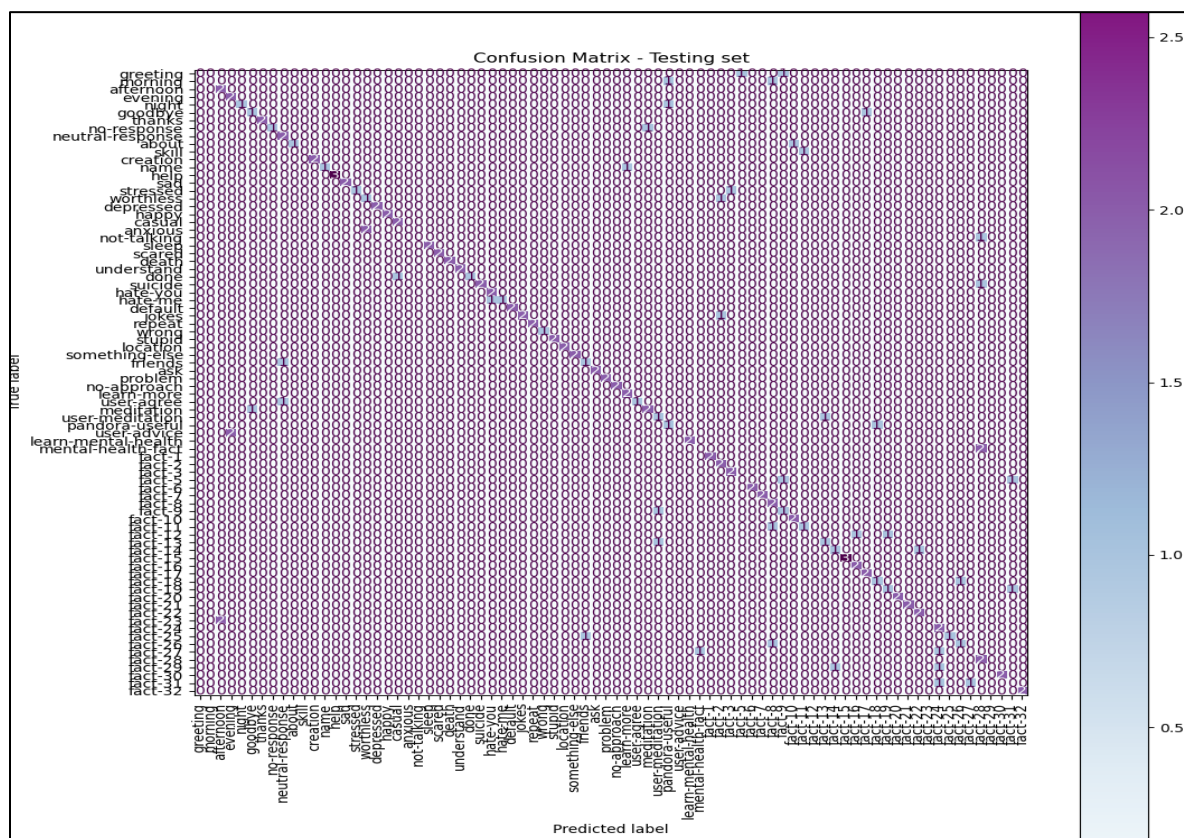
- Rows represent the **true labels** (actual user intents).
- Columns represent the **predicted labels** (what the model guessed).



- Each cell indicates the number of examples where a specific true label was predicted as a specific class.

A perfect model would have non-zero entries only on the diagonal (correct predictions), and zeros elsewhere. In this case, the confusion matrix showed that most of the predicted values were aligned along the diagonal, suggesting a high number of correct classifications. Only minor misclassifications were observed, and they were mostly between semantically close intents, which is common and understandable in complex language tasks.

By analysing the confusion matrix, we confirmed that the chatbot model performs well across most intents, including minority classes a direct result of earlier data augmentation and balancing efforts.



**Fig No. 4 Confusion Matrix**

accuracy			0.70	162
macro avg	0.67	0.69	0.66	162
weighted avg	0.68	0.70	0.67	162

In summary:

- **Overall accuracy is 70%**, meaning the chatbot correctly classifies user intents 7 out of 10 times.
- **Macro scores ( $\approx 66\text{--}69\%$ )** show that performance is decent even across rare classes.
- **Weighted scores ( $\approx 67\text{--}70\%$ )** confirm that the model does not excessively Favor majority classes.

The model demonstrates **strong generalization ability** across a diverse and balanced dataset.

Thus, the chatbot is performing well for a real-world mental health support scenario, especially considering the number of classes, varied user language patterns, and the complexity of emotional language.

## 8. DEPLOYMENT

After completing the training and evaluation phases, the next crucial step is **saving the trained model** for future use. In our chatbot project, the model was saved in a file with the .h5 extension a format commonly used to store trained Keras models.

Saving the model means that **all the learned parameters** (weights, biases, and structure) of the trained LSTM network are preserved. Instead of having to retrain the model from scratch every time it is needed, we can **simply load the saved .h5 file** and immediately use the model to make predictions. This saves significant time, computational resources, and ensures that the same version of the model is used consistently in deployment.

The .h5 file acts as a portable version of the trained model. It can easily be loaded into different environments, whether on a local server, a cloud platform, or embedded within a mobile application or web service. For chatbot deployment, this is especially important — the saved model can be integrated into the backend of a chatbot system (e.g., a Flask API, a Django server, or a direct Streamlit app) to classify user inputs and generate responses in real-time without needing retraining.

Moreover, saving the model allows flexibility for **future updates**. If further improvements are needed (e.g., retraining with more data, fine-tuning hyperparameters), a new model can be trained, saved again as a new version, and redeployed without disrupting the chatbot system.

In summary, by saving the trained model as a .h5 file, we achieve **efficient reuse, fast deployment, and easy scalability** of the mental health chatbot, making it ready for real-world integration into user-facing applications without repeated model training.

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