Project Report: AI Chatbot for Mental Health

Creating an AI Chatbot for Mental Health using deep learning and transfer learning involves the following steps:

**1. Project Overview:**

The primary objective of this project is to develop a robust, efficient, and scalable deep learning model capable of engaging in meaningful mental health conversations and providing supportive responses. This task is of paramount importance in today's society, where mental health issues such as anxiety, depression, and stress-related disorders are prevalent. Many individuals hesitate to seek professional help due to stigma, cost, or accessibility challenges. By utilizing deep learning techniques, we aim to provide individuals, mental health professionals, and researchers with a powerful tool to facilitate conversations and offer guidance in a supportive, empathetic manner.

The core of the model is based on Sequence-to-Sequence (Seq2Seq) models using Recurrent Neural Networks (RNNs), which are specifically designed for sequential data processing such as text-based conversations. These models have proven to be highly effective in understanding and generating human-like responses, making them an ideal choice for building an intelligent chatbot. The chatbot is trained to identify conversational patterns and respond appropriately, offering emotional support, stress-relief suggestions, and general mental well-being guidance. By processing user inputs, the system can determine the context of the conversation and generate relevant, thoughtful responses that encourage positive engagement and self-reflection.

To create this model, we have leveraged publicly available conversational datasets focused on mental health discussions. The goal is to train the chatbot using these datasets to ensure that it can generalize well across different user inputs and response styles. The datasets used for training consist of structured dialogues, where each response is carefully labeled and categorized, allowing the model to learn response generation patterns unique to mental health support. Through this process, we aim to develop a chatbot that can engage in meaningful discussions, providing users with a sense of companionship and support.

This AI-powered solution provides a significant advantage over traditional mental health resources, which may be limited by availability, accessibility, and personal comfort levels. Many individuals prefer expressing their feelings through anonymous digital platforms rather than seeking direct professional help. The chatbot serves as an immediate, 24/7 accessible solution, offering guidance and support whenever needed. By automating the conversational process using deep learning, this system offers a more scalable, objective, and accessible mental health support tool. The AI model is designed to process text efficiently, providing real-time feedback that allows users to engage in therapeutic discussions and access helpful resources when needed.

The system's efficiency is further enhanced by its scalability. As more conversational data becomes available or new mental health challenges emerge, the model can be retrained and updated to improve its response quality and contextual understanding. This adaptability makes the tool suitable for a variety of users, from individuals seeking emotional support to researchers studying AI-driven mental health interventions. The scalability of the system ensures that it can evolve along with the changing needs of mental health care, making it a valuable asset in promoting psychological well-being.

This report outlines the entire process of building the AI chatbot, from the initial stages of data collection to preprocessing, model architecture design, training, and evaluation. It delves into the challenges encountered during each phase of the project, such as data sensitivity, ensuring empathetic response generation, and optimizing a deep learning model for meaningful, human-like conversations. Additionally, the report discusses the lessons learned, strategies employed to overcome challenges, and the ongoing efforts to improve the chatbot’s effectiveness.

Beyond the development of the current model, this report also explores potential future enhancements that could make the system even more robust, flexible, and applicable to real-world mental health support scenarios. These enhancements could include integrating emotion recognition for more personalized interactions, incorporating real-time monitoring through voice-based conversations, and expanding the chatbot’s capabilities to provide multilingual support. With these advancements, the system could become an indispensable tool in the mental health sector, helping to provide accessible, reliable, and empathetic support to those in need.

In conclusion, this project provides an innovative AI-driven solution to the growing challenge of mental health support, combining the power of deep learning with the practical needs of mental health care. The continued development and refinement of the system promise to make a significant impact on mental health support, potentially revolutionizing how individuals interact with AI-driven mental health tools in the future.

**2. Key Concepts:**

**2.1 Deep Learning and Seq2Seq Models:**

Deep learning is a branch of machine learning that uses artificial neural networks to model complex patterns in large datasets. It has proven to be highly effective for natural language processing (NLP), speech recognition, and other applications that involve sequential data.

Sequence-to-Sequence (Seq2Seq) models are a class of deep learning models that specialize in processing sequential data, making them ideal for conversational AI and chatbot applications. They work by encoding input text into a fixed-length context vector and then decoding it to generate a coherent response.

**A typical Seq2Seq model consists of several components:**

• Encoder: The encoder processes the input text and converts it into a context vector, capturing the semantic meaning of the input sequence.

• Decoder: The decoder takes the context vector and generates a meaningful response based on the learned patterns from the training data.

• Attention Mechanism: The attention mechanism allows the decoder to focus on specific parts of the input sequence, improving the coherence and relevance of generated responses.

• Recurrent Neural Networks (RNNs): RNNs, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, are used to process sequential data and maintain long-term dependencies in conversations.

These components work together to form a robust chatbot that can generate contextually relevant, empathetic, and human-like responses, providing effective mental health support through AI-driven conversations.

**2.2 AI Chatbot for Mental Health:**

AI-driven mental health chatbots play a crucial role in providing accessible, immediate, and scalable emotional support. Many individuals face barriers to seeking professional help due to stigma, cost, or lack of availability. A chatbot that can engage in empathetic and meaningful conversations helps bridge this gap by offering real-time assistance, stress management techniques, and general mental well-being guidance. Traditional mental health support methods often require human intervention, which can be resource-intensive and inconsistent. By leveraging deep learning and natural language processing (NLP), we can automate conversational support and enhance accessibility for users in need.

Using deep learning techniques like Seq2Seq models with Recurrent Neural Networks (RNNs), the chatbot can process and generate text responses based on learned conversational patterns. The chatbot is trained on extensive datasets containing mental health dialogues, allowing it to recognize various user inputs and respond contextually. The system can provide personalized recommendations, coping strategies, and emotional reinforcement, ensuring users feel heard and supported.

This project focuses on developing an AI chatbot that can engage in mental health-related discussions and offer relevant responses based on user interactions. By leveraging Seq2Seq models with attention mechanisms, the chatbot improves its understanding of context, tone, and sentiment. It can recognize distress signals, suggest self-care techniques, and, if necessary, encourage users to seek professional assistance. This AI-powered approach ensures that mental health support is available to a broader audience, providing a proactive and scalable solution for emotional well-being.

**3. Steps in Building the Project:**

### ****3.1 Dataset Collection and Preprocessing:****

### Data Collection: In AI-driven mental health chatbots, acquiring a high-quality, diverse dataset of conversations is crucial for building an effective deep learning model. One of the primary challenges is ensuring that the dataset contains a wide variety of dialogues reflecting different mental health concerns. Publicly available datasets, such as counseling transcripts, mental health support conversations, and open-domain chatbot interactions, serve as an excellent foundation. These datasets contain structured conversations that help train the model to recognize user intent and generate meaningful responses. However, despite the availability of such datasets, challenges persist, such as ensuring data diversity, handling sensitive topics, and filtering out inappropriate or misleading responses. To enhance the model’s ability to generalize, additional curated datasets may be integrated.

### Data Preprocessing: Once a suitable dataset is obtained, the preprocessing phase plays a crucial role in ensuring the model can efficiently learn from the data. The goal is to transform raw conversational text into a structured format suitable for training. This involves tokenization, lowercasing, removing stop words, handling contractions, and dealing with special characters. Additionally, text sequences are padded to ensure uniform input lengths, and word embeddings are applied to convert text into numerical representations for the deep learning model.

### 3.2 ****Model Architecture****:

### Seq2Seq Model Design: The architecture of the deep learning model determines its ability to understand and generate human-like responses. Sequence-to-sequence (Seq2Seq) models, based on Recurrent Neural Networks (RNNs), are particularly well-suited for conversational AI. The architecture begins with an encoder-decoder structure where the encoder processes user input and converts it into a context vector, which the decoder then uses to generate a coherent response.

### To improve response quality, attention mechanisms are incorporated, allowing the model to focus on relevant parts of the input sequence while generating output. This ensures that responses are more contextually relevant and grammatically correct. Additionally, Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are employed to handle long-range dependencies and prevent vanishing gradient problems.

### At the final stage, the output of the decoder is passed through dense layers with a softmax activation function to predict the next word in the response. The model is fine-tuned using pre-trained embeddings such as GloVe or Word2Vec to enhance language understanding.

### Transfer Learning: Training an NLP model from scratch can be computationally expensive, particularly with limited data. To accelerate the training process and improve response quality, transfer learning is employed. Pre-trained transformer-based models such as GPT or BERT can be fine-tuned on the mental health dataset. These models have already learned rich language representations and can adapt more efficiently to the chatbot’s conversational domain.

### 3.3 ****Model Training****:

### Loss Function: The performance of the chatbot is measured using a loss function that quantifies the difference between the predicted response and the actual response. For sequence-based text generation tasks, the most common loss function used is categorical cross-entropy. This function evaluates the probability distribution of predicted words against the true sequence, encouraging the model to minimize the difference through backpropagation and weight updates.

### Optimizer: An effective optimizer is essential for adjusting the model’s parameters during training to minimize loss. Commonly used optimizers include Adam and Stochastic Gradient Descent (SGD). Adam is particularly popular for NLP tasks due to its adaptive learning rate, which adjusts dynamically during training. This helps the chatbot converge more quickly and generate high-quality responses.

### Training and Validation Split: To evaluate the performance of the model effectively and reduce the risk of overfitting, the dataset is split into separate training and validation sets. Typically, 80% of the data is used for training, while the remaining 20% is reserved for validation. Cross-validation techniques, such as k-fold cross-validation, may be employed to assess the model’s robustness. This ensures that the chatbot generalizes well and maintains consistency across different types of user inputs.

### 3.4 ****Model Evaluation****:

• **Accuracy:**  
The **accuracy** of the model is a fundamental metric that measures the proportion of correct predictions out of the total number of predictions made. While accuracy is a helpful metric, it may not always provide a complete picture, especially in cases where the dataset is imbalanced (e.g., some diseases are underrepresented).

• **Confusion Matrix:**  
To gain deeper insights into the model's performance, a **confusion matrix** is used to visualize the model’s predictions across different disease classes. The confusion matrix helps assess the model's effectiveness by showing the number of **true positives**, **false positives**, **true negatives**, and **false negatives** for each class. This provides a clearer picture of how well the model is distinguishing between different diseases and where it may be making errors.

• **Precision, Recall, and F1-Score:**  
In the context of imbalanced datasets, **precision**, **recall**, and the **F1-score** are crucial for evaluating model performance.

* **Precision** measures the proportion of true positives among all predicted positives, indicating how many of the predicted diseases were correctly identified.
* **Recall** measures the proportion of true positives among all actual positives, showing how well the model identifies all instances of a particular disease.
* The **F1-score** is the harmonic mean of precision and recall, providing a balanced metric when dealing with imbalanced classes. A higher F1-score indicates better performance in both precision and recall, which is particularly important in plant disease detection where false negatives (missing a disease) can be costly.

**4. Outcome of the Project:**

#### Accurate Response Generation: The deep learning model, developed using Sequence-to-Sequence (Seq2Seq) architecture with Recurrent Neural Networks (RNNs), has demonstrated exceptional accuracy in generating contextually appropriate and empathetic responses. By leveraging transfer learning and fine-tuning, the model has been able to utilize pre-trained knowledge from large conversational datasets, effectively overcoming the challenge of limited mental health dialogue data. This approach allows the model to generate meaningful responses even with smaller, specialized datasets, which is a significant advantage in the mental health domain where data sensitivity is a concern. The accuracy of the model has been rigorously tested using various evaluation metrics, ensuring that it can maintain coherent and engaging conversations. The ability of the chatbot to provide timely and relevant responses is crucial in offering emotional support and guiding users toward beneficial coping strategies.

#### Automated Conversational Support: The system's ability to automate mental health support represents a major breakthrough in digital counseling. Traditionally, seeking professional help for mental health concerns can be time-consuming, expensive, and stigmatized. By automating this process, the chatbot offers a faster and more efficient alternative, ensuring that users receive immediate assistance when they need it most. The chatbot allows users to engage in real-time conversations and receive personalized responses, empowering them to manage their emotions and mental well-being effectively. This reduction in manual effort also alleviates the burden on mental health professionals, enabling them to focus on high-priority cases while still benefiting from an AI-powered tool that supports general mental health queries. Furthermore, the model’s ability to recognize distress signals and provide crisis intervention recommendations enhances its utility as a supportive mental health companion.

#### Scalability: The scalability of the chatbot is one of its key strengths, allowing it to adapt to different mental health scenarios and user needs. Initially, the model has been trained on a specific dataset of mental health conversations, but its architecture supports continuous learning as more data becomes available. The chatbot can be fine-tuned to accommodate a broader range of mental health concerns, ensuring that it remains relevant and effective across diverse user interactions. Additionally, the system can be deployed across multiple platforms, including web, mobile applications, and social media integrations, making mental health support more accessible. By incorporating multilingual capabilities and domain-specific adaptations, the chatbot can cater to different cultural and linguistic backgrounds, ensuring that mental health resources are available to a wider audience.

#### User-Friendly Interface: One of the standout features of this project is its emphasis on accessibility and usability. The chatbot’s interface has been designed with simplicity and ease of use in mind, ensuring that users can engage in meaningful conversations without requiring technical expertise. The chatbot provides a seamless conversational experience with clear and intuitive feedback, making it easy for users to express their concerns and receive appropriate responses. This is particularly important for individuals who may be hesitant to seek traditional therapy but still require emotional support. Additionally, the system can integrate with mental health resources, offering users links to professional help when necessary. In the future, further enhancements could include voice-based interactions, real-time sentiment tracking, and expanded multilingual support to ensure that the chatbot remains a widely accessible and effective mental health tool.

#### 5.1 Data Quality and Labeling:

#### One of the foremost challenges in developing an effective mental health chatbot was ensuring the quality and accuracy of the dataset. Despite the availability of public conversational datasets, many contained inconsistencies that required careful attention. Some conversations lacked context, making it difficult for the model to learn meaningful patterns necessary for generating empathetic responses. Additionally, mislabeled dialogues were another common issue. For example, responses marked as supportive may have lacked true emotional depth, leading to misleading patterns in training.

#### Another challenge was the presence of noise in text-based conversations, such as irrelevant dialogue exchanges, informal language, or ambiguous user inputs that could mislead the chatbot. Data cleaning and preprocessing were crucial steps in addressing these problems. To mitigate these issues, dialogues were manually reviewed and corrected where necessary, ensuring that each response matched the intended emotional and contextual tone. Additionally, natural language processing (NLP) techniques such as stop-word removal, tokenization, and sentiment filtering were applied to enhance data quality, ensuring that the chatbot learned from relevant and well-structured conversations.

#### 5.2 Model Overfitting:

#### Overfitting is a well-known issue in deep learning, particularly when working with limited or imbalanced conversational datasets. Overfitting occurs when a model memorizes training data instead of learning generalizable patterns, leading to poor performance on real-world interactions. This was a significant challenge, especially given the complexity of human conversations and varying emotional expressions.

#### To mitigate overfitting, several strategies were employed. One of the primary techniques used was dropout, where a random subset of neurons is “dropped” during training to prevent the model from becoming too reliant on specific features. Additionally, batch normalization was incorporated to stabilize and speed up training by normalizing activations. Data augmentation techniques, such as paraphrasing existing dialogues and introducing synthetic conversation variations, were also used to improve the model’s robustness, ensuring that it generalizes well across diverse mental health discussions.

#### 5.3 Class Imbalance:

#### Another challenge encountered was class imbalance, which is common in conversational AI datasets where some types of responses are significantly more frequent than others. In mental health chatbot interactions, supportive and neutral responses tend to dominate, whereas crisis-related or highly empathetic responses appear less frequently. This imbalance can lead to biased predictions, where the chatbot over-predicts common response types and underperforms in sensitive or distress-related scenarios.

#### To address this issue, several methods were implemented to ensure the chatbot treated all response categories fairly. Class weighting was applied during training, adjusting the loss function to give more importance to underrepresented response types. Additionally, data resampling techniques such as Synthetic Minority Over-sampling Technique (SMOTE) were used to generate synthetic dialogues that enriched the training data, helping the model better recognize and generate empathetic responses even for less frequent conversational patterns.

#### ****5.4 Computational Resources:****

#### Training deep learning models on large conversational datasets is computationally intensive, requiring significant hardware resources. The chatbot’s architecture—particularly with multiple layers of recurrent networks and attention mechanisms—requires substantial memory and processing power, especially as dialogue complexity increasesp[5]. Training on a CPU alone would have been inefficient, leading to long training times and slower experimentation cycles.

#### To address this challenge, cloud-based services like Google Colab and Amazon Web Services (AWS) were used to speed up training. These platforms provide access to Graphics Processing Units (GPUs) optimized for parallel processing, enabling faster training and fine-tuning. This significantly reduced development time and allowed for extensive hyperparameter tuning and model iteration, ultimately improving chatbot performance. Cloud-based scalability also ensured that real-time deployment and chatbot updates could be managed efficiently as new conversations and interactions were incorporated into the dataset.

#### ****5.5 Real-World Deployment Challenges:****

While the chatbot was trained and evaluated successfully in a controlled environment, one of the long-term challenges is real-world deployment. In practical mental health support scenarios, factors such as ambiguous user input, slang, or varied emotional expressions can impact chatbot performance. Additionally, real-time interactions may require adaptation to ensure users receive accurate, context-aware, and empathetic responses.

To address this, ongoing research focuses on fine-tuning the model with additional real-world conversations and integrating transfer learning from pre-trained NLP models tailored for emotional intelligence. Furthermore, designing a user-friendly interface that works seamlessly across different devices—such as smartphones, web platforms, and messaging apps—remains an important challenge to ensure widespread adoption. Implementing ethical safeguards, such as crisis escalation protocols and real-time moderation, will also be crucial for ensuring responsible and effective mental health support through the chatbot[10].

**6. Future Enhancements:**

**6.1 Multi-Turn and Context-Aware Conversations:**

**Currently, the chatbot is designed to generate responses based on a single user query, providing a straightforward conversational flow. However, in real-world mental health support scenarios, users often engage in multi-turn conversations that require context retention. As part of future work, one of the key advancements would be the implementation of context-aware dialogue models, where the chatbot can remember previous interactions and maintain a coherent, ongoing conversation. This would improve the chatbot’s ability to offer more personalized and meaningful support. For instance, a user might mention feeling anxious in an earlier message, and the chatbot could recall this in a follow-up response, offering tailored coping strategies. This enhancement would make interactions feel more natural and effective for users seeking emotional support.**

**6.2 Integration with Voice Assistants and Smart Devices:**

**An exciting direction for future work is the integration of the mental health chatbot with emerging technologies such as voice assistants and smart devices. By deploying the chatbot on platforms like Google Assistant, Alexa, and Siri, users could engage in voice-based mental health conversations, making the tool more accessible to individuals who prefer speaking over typing. Additionally, integration with wearable devices that track stress levels, heart rate, and sleep patterns could enhance the chatbot’s ability to provide real-time emotional support. By analyzing this data, the chatbot could offer personalized recommendations, such as mindfulness exercises or relaxation techniques, based on the user’s physical and emotional state. With the ability to interact through various mediums, this integration would improve accessibility and engagement, ensuring that mental health support is available whenever and wherever users need it[4].**

**6.3 Expanding the Training Dataset:**

**To further improve the chatbot’s performance and versatility, expanding the dataset is crucial. Currently, the chatbot may be limited in its ability to handle diverse conversations, depending on the size and variety of dialogues it has been trained on. By incorporating more mental health discussions from different demographic groups, cultural contexts, and psychological conditions, the chatbot’s generalization capabilities can be significantly enhanced. A more diverse dataset would allow the model to generate more adaptive and empathetic responses when dealing with complex emotional expressions. Additionally, collecting real-world anonymized user interactions could help the chatbot improve its ability to recognize nuanced mental health concerns and provide better support. Expanding the dataset would not only improve response accuracy but also ensure that the chatbot can cater to a broader range of users and emotional situations**

**6.4 AI-Powered Personalized Coping Strategies:**

**Incorporating AI-powered personalized coping strategies would be a valuable enhancement to the chatbot. Upon identifying a specific emotional state, the chatbot could go beyond providing generic responses and offer customized mental health interventions. For example, if a user expresses stress, the chatbot could suggest tailored relaxation techniques, breathing exercises, or guided meditation based on their conversation history. These recommendations could be refined over time using reinforcement learning, ensuring that the chatbot adapts to the individual needs of each user. Additionally, the chatbot could integrate with online therapy platforms, providing users with professional mental health resources when necessary[8]. By extending its functionality to offer personalized self-care recommendations, the chatbot could become an even more effective tool in promoting mental well-being and emotional resilience, ultimately making mental health support more proactive and user-centric.**

**7. Conclusion:**

This project successfully demonstrates the transformative potential of deep learning techniques, particularly sequence-to-sequence (Seq2Seq) models and recurrent neural networks (RNNs), in revolutionizing mental health support. By leveraging these advanced AI methodologies, we have developed a highly effective and responsive chatbot capable of engaging in meaningful conversations[6], providing a powerful tool for individuals seeking mental health assistance. The model not only showcases the robustness of deep learning in addressing real-world mental health challenges, but also offers a practical solution for automating mental health support, which traditionally requires professional intervention and considerable resources.

Through the integration of a user-friendly interface, the chatbot offers real-time emotional support that is intuitive and accessible to a broad audience, from individuals with limited technical expertise to mental health professionals. This ease of use, combined with the chatbot’s ability to generate context-aware and empathetic responses, ensures that the technology can be implemented at scale to assist individuals in managing their mental well-being. Such automation is particularly beneficial for providing immediate assistance, which can be crucial for those experiencing distress, ultimately enhancing accessibility to mental health support while reducing the burden on human therapists.

Looking ahead, the project holds immense potential for further development and expansion. Future work will focus on broadening the chatbot’s capabilities by incorporating an even wider range of conversational contexts, allowing it to handle more diverse mental health concerns. By continuously updating the dataset with new dialogues and user interactions, the system will stay relevant and effective as mental health challenges evolve. In addition, the integration of real-time sentiment analysis and personalized response adaptation will allow the chatbot to provide more tailored and proactive support to users[3].

Moreover, there is significant potential to integrate this tool with other digital health technologies, such as wearable devices, mobile applications, and online therapy platforms, to create a comprehensive ecosystem for mental health management. This could enable users to receive timely and actionable insights, further optimizing their mental health practices and contributing to a more sustainable and efficient support system. By recognizing emotional patterns early and providing meaningful interventions, the chatbot can help reduce mental health crises, encourage self-care, and support better decision-making for users seeking emotional well-being.

In conclusion, the AI-powered mental health chatbot is a groundbreaking tool for modern mental health care, bringing cutting-edge AI solutions to the forefront of emotional support. As this technology continues to evolve, it holds the potential to redefine how mental health assistance is provided, monitored, and improved. With continued development, this chatbot could become an indispensable resource for individuals, therapists, and mental health organizations worldwide, ultimately contributing to the advancement of digital mental health solutions and the promotion of well-being.

In summary, the AI Chatbot for Mental Health is a valuable tool for providing scalable, accessible, and effective mental health support, and its continued development can lead to more sophisticated AI-driven solutions in mental health care.

**8.References**

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