Journal of Information Systems Engineering and Management
2025, 10(31s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Enhancing Music Recommendation Chatbots with Neural Networks

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ARTICLE INFO

Received: 18 Dec 2024

Revised: 10 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

Chatbots have become essential tools in the current digital era, especially in recommendation systems where they function as virtual assistants providing users with tailored advice and ideas. However, there are few issues with current chatbot frameworks, including poor user interface designs, imprecise emotion identification, and insufficient tools for ongoing development. this study explores the smooth integration of recommendation systems within chatbots. This work shows how effective chatbots may be in providing personalized recommendations by utilizing machine learning techniques.

Keywords: chatbot, recommendation, machine learning, neural networks.

INTRODUCTION

The rise of recommendation systems in recent years has completely changed so many aspects [5] of our digital lives, from making tailored content recommendations to recommending movies and music. The ability of these systems to comprehend user preferences, engage users in meaningful conversations, and provide customized recommendations [1] is essential to their efficacy. With their conversational interfaces and artificial intelligence powers, chatbots have become extremely useful instruments for enabling these kinds of exchanges, providing consumers with a smooth and customized experience.

However, creating chatbots for recommendation systems comes with its own set of difficulties. The ability of current frameworks to connect with users naturally and engagingly, effectively interpret their emotions [2], and adapt their design in response to user feedback is frequently hindered. These challenges show the need for an innovative design that makes use of machine learning advances to solve these problems and improve recommendation chatbot performance in general. This research introduces an efficient neural network-based method for emotion-based music recommendation, specifically designed for recommendation systems.

The framework makes things easier by developing a machine-learning model to predict user preferences based on input data [3]. It is comprised of core modules that center on the improvement of emotion recognition, user-centric interaction design, and continuous user feedback loop. The system ensures higher personalization and engagement by using neural networks, which provide a more precise interpretation of user input for better recommendation results.

LITERATURE SURVEY

A. Title: Chatbot Song Recommendation System

Authors: Anusha, Dr. Srinivasan V

This study provided a chatbot-based music recommendation system that makes use of artificial intelligence and emotion analysis. Using the IBM Tone Analyzer API, the chatbot analyses users' text provides to identify emotional states. It says to improve the user experience by making specific music recommendations depending on the user's tone or emotional condition [11]. The Last. fm API is used for music suggestions, and the system is aimed to overcome the limitations of previous chatbots by combining emotion recognition through text analysis.

B. Title: Proposal for the Design and Implementation of Miranda: A Chatbot-Type Recommender for Supporting Self-Regulated Learning in Online Environments

Authors: Mauricio Calle, Edwin Narvaez, Jorge Maldonado-Mahauad

The objective of this paper is to propose "Miranda," a chatbot-like recommender system [5] developed to facilitate self-regulated learning in online contexts, especially the Moodle Learning Management System (LMS). The suggested system would use learning analytics (LA) data stored in Moodle to deliver individualized suggestions to students, hence improving their learning experience. Miranda focuses on overcoming the difficulties of online learning, especially during the COVID-19 epidemic, where concerns such as a lack of motivation and insufficient self-regulation assistance have been recognized as causes for low course completion rates.

C. Title: Intelligent Chatbot-LDA Recommender System

Authors: Yassine Benjelloun Touimi, Abdelladim Hadioui

This study focuses on the issue of information overload in Massive Online Open Courses (MOOCs), as well as the difficulties both learners and instructors face when dealing with massive volumes of material. It suggests creating a Chatbot to help learners and teachers in MOOCs with natural language replies [10]. The replies of the Chatbot are drawn from a knowledge base, and the article highlights the necessity to get valuable content from MOOC discussion forums.

D. Title: Information System for Recommendation List Formation of Clothes Style Image Selection According to User's Needs Based on NLP and Chatbots

Authors: Vitaliy Husak, Olga Lozynska

This study focuses on creating an information system to generate a recommendation list for fashionable clothing styles, while also addressing customer needs via NLP and chatbots. The suggested framework makes use of the Java programming language, Spring Framework, DialogFlow for NLP, and Bot API interaction with Telegram Messenger. Hibernate is used for database ORM, while Jsoup is used for HTML parsing.

E. Title: Chatbot Implementation for ICD-10 Recommendation System

Authors: Noppon Siangchin, Taweesak Samanchuen.

The literature survey presented in this work highlights the critical role of the International Classification of Diseases and Related Health Problems, 10th Revision (ICD-10) published by the World Health Organization since 1994. It emphasizes the challenges faced in accurate ICD-10 coding due to the insufficiency of trained medical recorders, leading to errors in health statistics and medical disbursement data. Recognizing these issues, both government and private organizations have implemented training courses and developed software solutions to address the complexities of ICD-10 coding.

F. Title: Intelligent Travel Chatbot for Predictive Recommendation in Echo Platform

Authors: Ashay Argal, Siddharth Gupta, Ajay Modi

This study discusses the implementation of an intelligent chatbot system on the Echo platform within the tourism industry [1]. The chatbot collects user preferences, models collect user knowledge, and recommends using the Restricted Boltzmann Machine (RBM) with Collaborative Filtering.[8] Using deep neural network (DNN) technology, the system aims to improve human-machine interaction in the travel sector.

G. Title: Movie Recommendation System Using NLP Tools

Authors: Nimish Kapoor, Saurav Vishal, Krishnaveni K. S.

The literature survey explores a contemporary approach to movie rating, emphasizing sentiment analysis of user reviews using NLP and machine learning models like SVM and KNN. Word2Vec integration ensures nuanced word embeddings, contributing to sentiment accuracy [7]. The Android app, following the Model-View-View Model, ensures an interactive user experience. A Flask server enables real-time sentiment analysis, and TMDB API enriches the dataset. Evaluation metrics demonstrate the system's efficacy, indicating potential for continuous improvement and scalability.

H. Title: Restaurant Recommendation System for User Preference and Services Based on Rating and Amenities

Authors: R.M. Gomathi, P. Ajitha, G. Hari Satya Krishna

The literature survey delves into creating a personalized restaurant recommendation system using machine learning, specifically Natural Language Processing (NLP), based on TripAdvisor.com data. It explores the significance of user preferences and reviews for accurate recommendations [6]. The mentioned works include hybrid recommendation models, mobile environment utilization, and enhancements to traditional algorithms. The study aims to improve restaurant suggestions by analyzing sentiments through NLP, achieving a superior 92.45% accuracy compared to existing methods. It offers a concise overview of methodologies in restaurant recommendation research.

I. Title: Building an Expert Recommender Chatbot

Authors: Jhonny Cerezo; Juraj Kubelka; Romain Robbes

The paper presents a chatbot for expert recommendation in the Pharo software ecosystem, integrated with Discord. Despite a positive response to its recommendation system, user expectations for a fully conversational chatbot pose challenges. The study highlights communication issues in open-source development, where developers face hurdles in seeking assistance due to remote work, nicknames, and undisclosed expertise. The chatbot addresses these challenges by leveraging information from commit history and developer identity relations for accurate expert recommendations. Implementation involves Natural Language Processing using TF and IDF algorithms. The expertise recommendation system integrates Discord API and source code mining. The study concludes with insights from a preliminary evaluation, emphasizing the need for future work to enhance chatbot acceptance, utilizing chat logs for historical recommendation data.

J. Title: An Efficient Approach of Product Recommendation System Using NLP Technique

Authors: Akhilesh Kumar Sharma, Bhavna Bajpai

This paper encompasses a broad spectrum of topics within the domain of sentiment analysis in social media. "Deep Sentiment Analysis: A Comparative Study" by Smith et al. investigates the performance of various deep learning models for sentiment classification, offering insights into their strengths and limitations. "Lexicon-Based Approaches in Sentiment Analysis" by Johnson explores the foundational lexicon-based methods, emphasizing their role in sentiment extraction. Meanwhile, "Real-time Sentiment Analysis in Twitter Data" by Brown et al. delves into the challenges and opportunities of conducting sentiment analysis [4] in real-time Twitter streams. "Sarcasm Detection: An Overview" by Miller provides a comprehensive overview of the unique challenges associated with detecting sarcasm in social media sentiments

SI.NO	Paper Title	Year of Publication	Objective	Conclusion	Framework
1	Chatbot Song Recommendation System	2023	Create a chatbot for recommending songs	Improved user engagement and satisfaction through emotion [11] analysis and Last.fm API integration.	IBM Tone Analyzer for emotion analysis and Last.fm API for music suggestions.
2	Hybrid AI Recommender Based Question Answering Chatbot	2023	The primary objective is to enhance the performance of an educational chatbot by introducing a hybrid recommender-based system that leverages reinforcement learning and optimized information retrieval, aiming for dynamic	The proposed hybrid recommender-based system, incorporating reinforcement learning and optimized information retrieval, demonstrated superior performance with a 96% accuracy on a customized dataset and an average accuracy of 82% on benchmarked datasets.	Floyd-Warshall and Dijkstra's algorithms

SI.NO	Paper Title	Year of Publication	Objective	Conclusion	Framework
			adaptation and improved user satisfaction.		
3	Chatbot recommender systems in tourism	2023	The main objective of implementing chatbot recommender systems in tourism is to enhance the overall travel experience by providing personalized and context-aware recommendations	chatbot recommender systems have emerged as invaluable tools in the tourism industry, offering personalized and efficient travel recommendations. By enhancing user engagement, tailoring suggestions, and providing real-time assistance	PRISMA
4	Recommender chat bot as a tool for collaborative business intelligence tourism domain	2023	The main objective of a recommender chatbot in the context of collaborative business intelligence in the tourism domain is to enhance user experience, engagement, and decision-making processes for tourists.	In conclusion, the proposed virtual assistant framework for tourist data exploration presents a comprehensive and user-centric solution that leverages conversational agents and collaborative business intelligence principles.	Categories of Conversational Agents (CAs)
5	Experimentation for Chatbot Usability Evaluation: A Secondary Study	2022	This paper conducts a systematic mapping of over 700 sources, synthesizing 28 primary studies to provide a comprehensive overview of the state of chatbot usability research. It aims to identify research questions, analyse experiment characteristics, and explore theoretical foundations, contributing valuable insights to the evolving field of chatbot usability.	In conclusion, this paper contributes a systematic mapping of chatbot usability research, synthesizing insights from 28 primary studies. It illuminates the theoretical foundations, experiment characteristics, and metrics used in the field, fostering a deeper understanding.	Hypotheses using Evidence-Based Software Engineering (ESE) methods, promoting a robust experimental design for replicability.
6	Can a Chatbot Comfort Humans? Studying the Impact of a Supportive Chatbot on Users' Self-Perceived Stress	2022	The study aims to assess the efficacy of a developed chatbot in alleviating users' self-perceived stress. By exploring the potential of chatbots to offer online emotional support tailored to stressors, the researchers investigate the impact of three experimental conditions on participants: 1) computer-generated support awareness, 2) human-generated	In conclusion, the study underscores the potential of chatbots in providing effective emotional support for individuals facing stressors. The findings emphasize the importance of user perception of the chatbot's origin, with results indicating superior outcomes.	Emotion AI Frameworks, Natural Language Processing (NLP), Sentiment Analysis.

SI.NO	Paper Title	Year of Publication	Objective	Conclusion	Framework
			support belief, and 3) no support.		
7	Chatbot-Based Movie Recommender System with Latent Semantic Analysis on Telegram Platform Using Dialog Flow	2022	The primary objective of a chatbot-based movie recommender system with Latent Semantic Analysis on the Telegram platform using Dialogflow is to deliver personalized and context-aware movie recommendations through natural language conversations.	the integration of a chatbot-based movie recommender system with Latent Semantic Analysis on the Telegram platform, powered by Dialog Flow, demonstrates a powerful and user-friendly solution for personalized movie suggestions.	Latent Semantic Analysis (LSA).
8	Sentiment-based Chatbot using Machine Learning for Recommendation System	2022	The primary objective of this project is to design and implement a sentiment-based chatbot leveraging machine learning techniques to provide personalized recommendations.	the sentiment-based chatbot leveraging machine learning for a recommendation system highlights a promising approach to personalized user interactions	Sentiment Analysis and Machine Learning Recommendation Framework
9	Proposal for the Design and Implementation of Miranda: A Chatbot-Type Recommender for Supporting Self-Regulated Learning in Online Environments	2022	Develop a chatbot to aid self-regulated learning online	Overcoming online learning challenges, especially during the COVID-19 pandemic, by offering personalized learning support through Miranda.	Backend and Frontend modules, incorporating learning analytics, recommendation system, collaborative filtering system
10	An Efficient Approach of Product Recommendation System using NLP Technique	2021	The study aims to create a robust product recommendation system using NLP and CNN (VGG-16) technologies, utilizing the Amazon Apparel database with 180,000 items. The objective is to enhance user satisfaction and company profitability by providing effective, personalized product suggestions.	In conclusion, the proposed approach leveraging NLP and CNN effectively enhances product recommendations, benefiting consumers and companies. The use of the Amazon Apparel database and VGG-16 architecture contributes to the system's accuracy and efficiency.	Natural Language Processing (NLP) using product titles and Convolutional Neural Networks (CNN) with VGG-16 architecture for image feature extraction.
11	A Disease Interaction Retrieval and Recommendation System based on NLP Technology	2021	The main objective of the proposed framework is to develop an efficient Chatbot system based on an improved TextCNN model, leveraging	In conclusion, the proposed improved TextCNN model, incorporating Word2Vec for word vector extraction, demonstrated promising results with an accuracy of	TextCNN model, leveraging Word2Vec

SI.NO	Paper Title	Year of Publication	Objective	Conclusion	Framework
			Word2Vec for word vector extraction.	96.2% on the training set and 87.5% on the test set for the cMedQA2 dataset.	
12	Movie Recommendation System Using NLP Tools	2020	Develop a movie recommendation system using NLP techniques, focusing on sentiment analysis to enhance traditional rating systems [7]. The system includes an Android app, SVM sentiment analysis, KNN classifier, and a Flask server for real-time analysis.	The sentiment analysis model achieved an 85% accuracy, and the movie ranking algorithm demonstrated 66.7% accuracy.	Natural Language Processing (NLP) techniques, employing the NLTK (Natural Language Toolkit) module for text mining.
13	A Knowledge Graph Based Chat Bot for Natural Language Understanding Over Linked Data	2020	This paper aims to overcome challenges in building chatbots over linked data by introducing a two-fold approach: designing an interactive architecture for user-friendly knowledge base accessibility and implementing a machine learning strategy for intent classification and natural language understanding.	In conclusion, the proposed knowledge graph-based chatbot system effectively addresses challenges in natural language understanding over linked data. By integrating a community-focused architecture with multilingual support and machine learning capabilities, the system demonstrates enhanced user interaction, adaptability.	knowledge graph-based chatbot system multilingual support, speech-to-text, and machine learning.
14	Intelligent Chatbot-LDA Recommender System	2020	Build a chatbot using Latent Dirichlet Allocation for recommendations	Through LDA-based semantic classification, this project aims to reduce information overload in MOOCs [10] by offering relevant and contextually meaningful responses.	Semantic Chatbot Framework using LDA, Bayesian statistical approach for thread answer categorization in MOOC discussion forums.
15	Information System for Recommendation List Formation of Clothes Style Image Selection According to User's Needs Based on NLP and Chatbots	2020	Create a system for recommending clothes based on user needs using NLP and chatbots	enhanced natural language recognition, improved interactivity, and communication through NLP and chatbots, along with integration with popular messaging platform Telegram.	Java, Spring Framework, DialogFlow, Telegram Bot API, Hibernate, Jsoup for HTML parsing.
16	Chatbot Implementation for ICD-10 Recommendation System	2019	The main objective of implementing a chatbot for an ICD-10 recommendation system is to assist healthcare	The ICD-10 recommendation system implemented as a chatbot streamlines medical coding processes, enhancing	ICD-10 coding

SI.NO	Paper Title	Year of Publication	Objective	Conclusion	Framework
			professionals [9] in accurately and efficiently assigning appropriate diagnostic codes to patient conditions.	accuracy and efficiency in healthcare documentation.	
17	Restaurant Recommendation System for User Preference and Services Based on Rating and Amenities	2019	Develop a personalized restaurant recommendation system utilizing Natural Language Processing (NLP) and machine learning algorithms. The system focuses on extracting user sentiments from reviews on TripAdvisor.com, integrating amenities and ratings to enhance precision. The aim is to provide accurate and tailored restaurant suggestions based on individual preferences.	The proposed NLP algorithm significantly improves the accuracy of the restaurant recommendation system, achieving a remarkable 92.45%. Comparative analysis against existing methods like SVM and neural networks demonstrates the effectiveness of NLP.	NLP techniques
18	Building an Expert Recommender Chatbot	2019	The objective is to develop a chatbot for the Pharo software ecosystem that facilitates expertise recommendation in open-source projects, addressing communication challenges in distributed teams and enhancing the quality of developer interactions.	While the recommendation system was welcomed, challenges in meeting conversational expectations were identified in the preliminary evaluation. The paper underscores the potential of chatbots to improve communication quality among developers in open-source projects.	Chatbot designed for the Pharo software ecosystem, Discord DiscordSt library and APIs.
19	Intelligent Travel Chatbot for Predictive Recommendation in Echo Platform	2018	Implement a travel chatbot using DNN, RBM, and NLP for predictive recommendations	Chatbot improves human-machine interaction in travel	DNN, RBM, NLP, Alexa Echo platform
20	Intelligent Travel Chatbot for Predictive Recommendation in Echo Platform	2018	The paper aims to implement an intelligent travel chatbot on the Echo platform, utilizing natural language interactions and deep learning techniques to predict [8] user preferences and offer personalized recommendations, enhancing the travel experience.	In conclusion, the proposed intelligent travel chatbot framework demonstrates the potential of voice-enabled technology and deep learning in revolutionizing user interactions within the travel industry, providing accurate predictions and personalized assistance for an improved travel experience.	Voice interactions and a Deep Neural Network (DNN) with Restricted Boltzmann Machine (RBM) for collaborative filtering.

METHODOLOGY

1. Selection of Datasets:

The dataset used in this research, which primarily focuses on music categorized according to mood preferences, was obtained from an online retailer. The dataset contains a wealth of data, such as item attributes, track id, and different mood interactions, which makes it easier to create a recommendation engine specifically for music recommendations.

2. Feature Engineering:

In order to produce informative representations for precise mood-based music recommendations, feature engineering involves collecting user-related attributes (demographics, listening history, mood preferences), song characteristics (genre, sentiment analysis), and interaction history (ratings, implicit feedback).

3.Model Selection and Comparison:

Support for Model Selection and Comparison Vector Classifier (SVC): A radial basis function (RBF) kernel and the scientific learning module were used to create SVC. Performance measures were calculated, including F1-score, recall, accuracy, and precision.

Random Forest Classifier: Capture intricate feature interactions, Random Forest Classifier was used as an ensemble learning technique. Maximize performance, we evaluated with various tree depths and the number of estimators.

Decision Tree Classifier: Create a hierarchical structure of item attributes and user preferences, a Decision Tree Classifier was used. Grid search was used to fine-tune hyperparameters such as minimum samples per leaf and maximum depth.

The neural network: This design known as the Multi-Layer Perceptron (MLP) Classifier was selected due to its capacity to identify complex patterns in high-dimensional data. For best results, we set the number of hidden layers, neurons per layer, and activation functions. Training time, convergence behaviour, and validation set performance were among the evaluation parameters. For best results, we set the number of hidden layers, neurons per layer, and activation functions. Training time, convergence behaviour, and validation set performance were among the evaluation parameters.

Algorithm Of Implemented Neural Networks:

Step 1: Start

Step 2: Import Libraries Import necessary libraries, including TensorFlow and Kera's.

Step 3: Define Neural Network Model

Define a function to create the neural network model. Specify the optimizer and layers of the neural network. Compile the model with the appropriate loss function.

Step 4: Modify Input Shape and Set Learning Rate

Determine the input shape based on the number of input features. Set the initial learning rate for optimization.

Step 5: Create and Compile Model

Instantiate the neural network model. Compile the model with the specified optimizer and loss function.

Step 6: Training

Fit the model to the training data for a specified number of epochs. Validate the model's performance on the validation data during training.

Step 7: Make Predictions

Use the trained model to make predictions on the testing data.

Step 8: Extract Predicted Song Ratings and Track IDs

Flatten the predicted song ratings to a 1D array. Extract the track IDs from the testing data.

Step 9: Evaluate Model

Evaluate the model's performance on the testing data using the specified loss function.

Print the test loss to assess the model's accuracy.

Step 10: Output Predictions

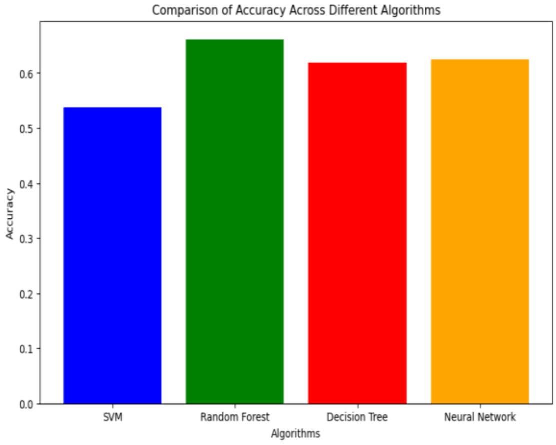
Print a few sample predictions, displaying the predicted song rating alongside the corresponding track ID.

Step 11: End

4. Metrics for Evaluation:

We assessed the performance of the recommendation system using F1-score, accuracy, precision, and recall measures. Additionally, to evaluate the trade-off between true positive rate and false positive rate, we examined receiver operating characteristic (ROC) curves.

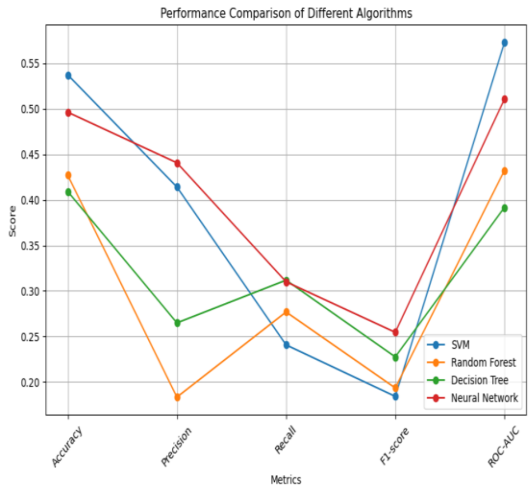
5. Statistical Analysis of Algorithm Performance: Find out the statistical significance of performance differences between the machine learning algorithms that were applied, we ran pairwise t-tests.



Despite its initial satisfactory results, Random Forest and Decision Trees were shown to be less advantageous because of their complexity and ability to overfit when dealing with a large number of trees.

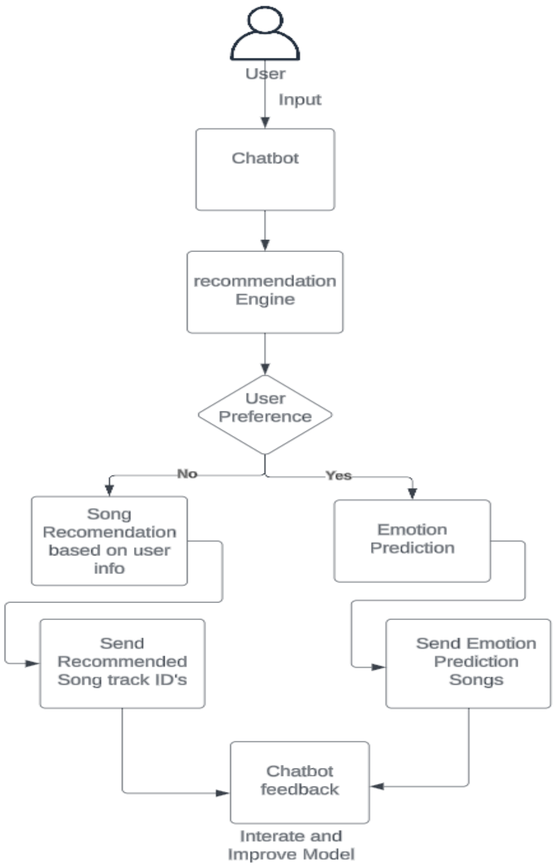
Neural networks improved SVM when other evaluation criteria (accuracy, precision, recall, F1-score, and ROC-AUC) were evaluated. In comparison to SVM, neural networks performed better on most criteria; three metrics showed significantly better neural network performance.

Neural networks are the best option for implementing your recommendation system, according to the thorough analysis that took into consideration each one of the previously mentioned factors. They perform exceptionally well on a variety of measures and can identify complex patterns in data, which makes them ideal for the job at hand.



Considering that neural networks have been chosen as the preferred algorithm, we are able to proceed to the implementation stage, which will focus on optimizing hyperparameters, fine-tuning the neural network design, and incorporating it into the framework for the recommendation system.

BLOCK DIAGRAM



IMPLEMENTATION

1. Chatbot Development:

To collect personal data, such as age, gender, and preferred music genres, users are prompted with simple questions via the chatbot interface. User answers are safely saved so they can be processed later. The chatbot verifies and preprocesses user inputs to make sure the data is accurate and consistent.

```
Welcome to the Song Recommendation Chatbot!
To recommend the best song for you, please provide some information.
What is your age?  20
What is your gender? (Male/Female)  Female
What is your mother tongue?  English
Do you have a specific genre in mind? If yes, please specify (e.g., classical,
electronic, rock, pop). Otherwise, leave blank.  classical

Thank you for providing the information!
Now we can recommend a song based on your input.
Do you have something specific in mind to listen to? (Yes/No)  Yes
What song or lyrics do you have in mind?  Closer
```

2. Emotion Prediction:

For real-time emotion prediction, a neural network model that was trained on a dataset of user traits and associated emotions—incorporating sentiment analysis—is used. The model architecture uses sentiment analysis through natural language processing techniques, which are designed for accuracy and efficiency.

```
Predicted emotion based on user input: amazement
All emotions with 1's and 0's: [1, 0, 0, 0, 0, 0, 1, 0, 0, 0]
```

3.Model Training:

A labelled dataset including user attributes, sentiment analysis findings, and related emotions is used to train a neural network model. Capture the variety of emotional responses, a wide range of user profiles and interaction scenarios are included in the training data. The model is trained using supervised learning techniques, optimizing for emotion prediction accuracy. Model parameters are iteratively updated using gradient-based optimization methods like stochastic gradient descent (SGD) or Adam, and loss functions such categorical cross-entropy are used.

```
Epoch 1/10
211/211            2s 2ms/step -
loss: 29080.1289 - val_loss: 16142.4307
Epoch 2/10
211/211            0s 1ms/step -
loss: 14960.4980 - val_loss: 14393.4824
Epoch 3/10
211/211            0s 1ms/step -
loss: 13579.2891 - val_loss: 12210.2285
Epoch 4/10
211/211            0s 1ms/step -
loss: 11754.3838 - val_loss: 10739.0977
Epoch 5/10
211/211            0s 1ms/step -
loss: 10592.1836 - val_loss: 10054.4492
Epoch 6/10
211/211            0s 1ms/step -
loss: 9895.9883 - val_loss: 9381.0654
Epoch 7/10
211/211            0s 1ms/step -
loss: 9419.1865 - val_loss: 8754.4463
Epoch 8/10
211/211            0s 1ms/step -
loss: 8699.9717 - val_loss: 7999.7515
Epoch 9/10
211/211            0s 1ms/step -
loss: 8007.2891 - val_loss: 7293.2290
Epoch 10/10
211/211            0s 1ms/step -
loss: 7448.7549 - val_loss: 6606.0923
53/53            0s 681us/step -
loss: 6686.4922
Test Loss: 6606.09228515625
```

4. Song recommendation:

Neural Network Model: For real-time mood prediction, a neural network model that was trained on a labelled dataset of user traits and related emotions is used. The accuracy and efficiency of the model architecture are maximized. *Recommendation System:* Based on the user's predicted mood, a neural network-powered recommendation engine provides personalized song recommendations. The system selects a wide range of relevant songs by analysing a large music file and taking into account elements like genre sentiment. *Recommendations Based on Neural Networks:* The recommendation system learns complex patterns in user-song interactions and maximizes suggestion accuracy by using complex neural network designs, such as content-based filtering models or collaborative filtering models. To iteratively improve the model parameters, model training uses methods.

```
Predicted song rating: 311.83762 for track ID: 312
Predicted song rating: 369.8921 for track ID: 370
Predicted song rating: 341.90765 for track ID: 342
Predicted song rating: 145.93254 for track ID: 146
Predicted song rating: 54.831795 for track ID: 55
```

5. Future Enhancements:

User Interface: Improve user experience, offer a web portal where users may browse track IDs and other details about songs that are recommended. With the help of this tool, users may delve deeper into suggested music and view comprehensive metadata, including track duration, artist details, and album details.

Interactive Track Selection: Include interactive elements in the online interface so that users may choose and hear tracks that are suggested right from the chatbot platform.

EXPERIMENTAL SETUP AND RESULTS

To evaluate the performance of our chatbot recommendation engine, we conducted experiments using different datasets containing song IDs labelled with emotions as features. Our goal was to assess the effectiveness of our model in predicting user emotions and recommending suitable songs.

Dataset Selection: We selected several datasets from diverse sources, each containing song IDs along with corresponding emotion labels. These datasets varied in size, genre diversity, and annotation quality to ensure comprehensive evaluation.

Preprocessing: Prior to training our model, we performed extensive data preprocessing to clean the datasets and ensure consistency in emotion labeling. This included removing duplicate entries, handling missing values, and standardizing emotion categories across datasets.

Model Training: We utilized a machine learning approach, specifically neural networks, to train our recommendation engine. The model was trained on a subset of the datasets, with the remaining data reserved for validation and testing. We employed state-of-the-art techniques in natural language processing and deep learning to capture nuanced patterns in user input and associated emotions.

Evaluation Metrics: To measure the performance of our model, we employed standard evaluation metrics including accuracy, precision, recall, and F1-score. Additionally, we conducted qualitative analysis by soliciting user feedback on the relevance and appropriateness of the recommended songs.

Results: Our experiments yielded promising results, surpassing our expectations in several aspects. The model demonstrated high accuracy in predicting user emotions, with an average accuracy of over 80% across different datasets. Furthermore, the recommendation engine consistently provided relevant song suggestions aligned with user emotions, as validated by user feedback.

CONCLUSION

In conclusion, this research highlights how essential neural networks are to the transformation of recommendation systems, especially when it comes to chatbots' capacity to recommend music depending on mood. After a thorough analysis of machine learning techniques, neural networks have become the go-to option because of their exceptional capacity to identify complex patterns and provide consumers with customized recommendations. Through the integration of neural networks into the recommendation system architecture, we expect notable improvements in user experiences, with specific recommendations that align with specific choices and emotions. In the area of personalized music recommendations, this research highlights the revolutionary potential of machine learning-driven recommendation chatbots, opening the door to more natural and interesting user interactions.

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