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Hybrid Intelligence for Healthcare: Transforming Tomorrow's Mental Health Diagnosis with Multi-Model Architecture

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Abstract

These research studies are focused on the applicability of traditional machine learning models such as logistic regression to advanced transformer models such as LLaMA 3 to enhance the prediction of diseases through easier access to healthcare services. Trained with artificial healthcare data related to mental health conditions, the hybrid model was better in accuracy and user engagement than standalone models. The system would allow for real-time user-friendly health insights through a chatbot interface owing to the structured prediction logistic regression capabilities and conversational power of the transformer. It would bring complex medical data and a patient in closer proximity, perhaps even in telemedicine or remote health monitoring. The hybrid model studied here shows the transformative role AI can play in healthcare by both predictive accuracy and user experience and suggests that such hybrid models should democratize access to healthcare for patients and enhance the provider's decision-making.

Keywords: Disease Prediction, Logistic Regression, Transformer Model, LLaMA 3, Mental Health, Hybrid Model, Healthcare Chatbot

Introduction :

1. Background:

AI revolutionizes healthcare with Large Language Models and generative AI (Rajkomar et al., 2019). Transfigurations have been very prevalent in the applications of mental health, for example, in early detection and monitoring advanced algorithms revealed promising results (Zhou & Jiang, 2023). This paper demonstrates a hybrid model that merges logistic regression and LLaMA 3 to augment the algorithm with better prospects for disease prediction through conversational interfaces.

2. Research Question:

Does the combination of a traditional machine learning model and a transformer model enhance the precision of the forecast of diseases, or make health information more accessible to patients? Discuss creating an easy access point that will serve both patients and healthcare professionals.

3. Significance:

This paper aims to improve health care through better prediction of diseases as well as patient engagement catalyzers for, in particular, mental health under a hybrid approach toward personalized medicine, to stamp out stigma, and as a tool where learning may always occur from patient interaction (Gupta et al., 2022).

4. Structure:

The LLaMA 3 will introduce logistic regression, which combines the best of predictive ability and conversational applications in predicting mental health disorders. This hybrid model offers a balance between clinical relevance and the accessibility of healthcare data.

Literature Review:

The recent developments of transformer models by Zhou et al. (2021) have dramatically advanced the general area of mental health prognosis in light of machine learning integration with social media data. Sun et al. (2023) demonstrated how deep learning approaches using natural language processing have improved mental health assessment. The prospects are promising as it appears to support innovative changes; however, the structured data and the real-time mental health assessment still remain apart (Cho et al., 2023).

Vaswani et al. (2017) presented transformer models, which took current approaches to the revolution of contextual understanding and, subsequently to mental health applications. Guntuku et al. (2020) demonstrated how transformers could be especially applied to unstructured social media text for the identification of depression and anxiety. The collection of mental health data from social media was comprehensively covered in terms of ethical considerations (Benton et al., 2017), with Tsakalidis et al. (2020) implying an emerging research agenda on large-scale mental health monitoring.

Conway and O'Connor (2016) highlighted the available sources of Twitter for public health surveillance, particularly regarding psychiatric health and illness trends. Yin and Wang (2016) summarized updating the algorithms for representing emotional states on social media using robust computational methods for mental health data. Lyu et al. (2021) generalized the transformer models to classify text involving mental health conditions.

Methodology:

- **Description of the Research Design**

This study was practically applied and of a quantitative approach since it entails combining the traditional machine learning methods, not forgetting logistic regression, with transformer models such as LLaMA 3 in healthcare disease prediction. The targeted diseases included Obsessive-compulsive disorder, major depressive disorder, bipolar disorder, and stress, and for each, synthetic data was created. The aim will be to predict the risk through logistic regression. Then, the outcome results will be fed into a nontechnical user in the form of a chatbot interface that will be supported by Botpress- a strong platform that can facilitate both accuracy and usability.

(The flowchart here is to visually demonstrate the workflow for 3 diseases, starting from user query generation to disease prediction, chatbot interaction, and consultancy booking)

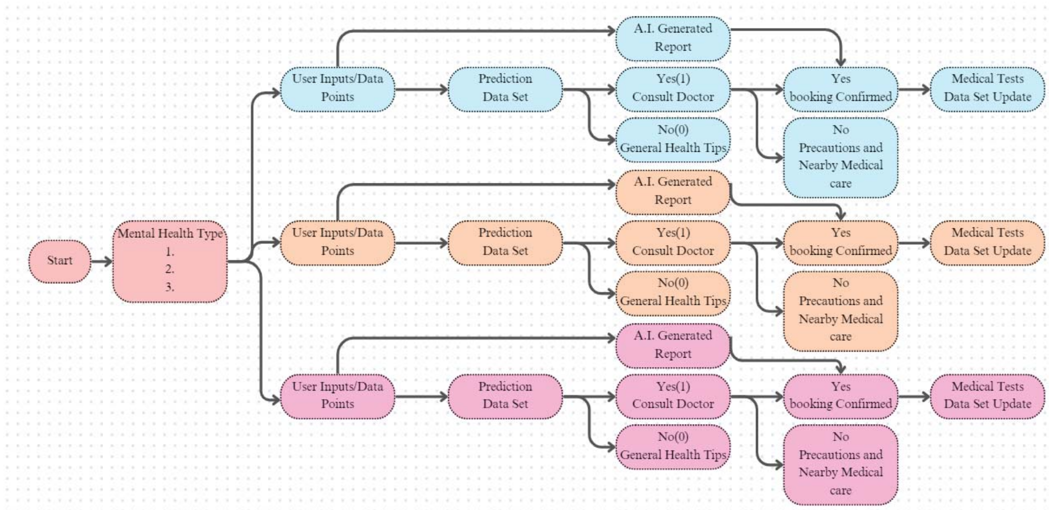

Figure 1. Workflow of the process in 'Botpress'.

- **Explanation of data collection methods.**

This study uses synthetic data to simulate real-world healthcare datasets, ensuring privacy and ethical considerations before deploying actual data. The synthetic dataset includes key attributes for predicting four diseases: obsessive-compulsive disorder, major depression, bipolar disorder, and stress, modeled to reflect realistic healthcare patterns.

Synthetic Data Generation Process

These are generated using Python-based libraries called Scikit-learn, Numpy, and Pandas. For every feature, statistical distributions are used appropriately to simulate the characteristics of real-world user-oriented healthcare.

The data is then formatted in a CSV format that includes features (input variables) along with their target variable corresponding to whether a patient suffers from a specific disease or not.

Dataset Size and Distribution

To eliminate the biases of the above model in disease prediction, a synthetic dataset of 313 records was prepared, equally distributed over four diseases. The remaining 80% is used to train the logistic regression model, and 20% is kept aside to be utilized for testing and validation for proper fitting of the model as well as preventing it from overfitting. The performance of the model is measured in terms of metrics such as accuracy, precision, recall, and F1 score.

- **Description of data analysis techniques**

Among the two major models utilized for disease prediction in the current study, the logistic regression machine learning algorithm was used as the first pass of initial analysis and model training on the dataset. Further, a conversation prediction was applied based on user queries in the platform, which is Botpress, with the transformer model known as LLaMA 3.

Logistic Regression for Data Analysis

This analysis uses logistic regression on synthetically generated healthcare datasets. The synthetic dataset contains some features associated with the four diseases age, family history, hours of sleep, and other diagnostic indicators. The logistic regression model is first trained and then tested to predict the likelihood of disease occurrence with the help of input features.

Transformer Model for Final Prediction in Botpress

Once the machine learning model is trained and tested, the outcome of it is merged into the knowledge base of Botpress. The logistic regression model is a foundation for predicting diseases, but the final user interaction happens through a transformer model-LLaMA 3, which enables dynamic and interactive predictions according to a question asked by a user.

Results:

1. Model Performance Data

- **Accuracy Score**: The accuracy score represents the percentage of correct predictions made by the model.

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(Accuracy of the Regression Model is 92%)

- **Precision, Recall, and F1-Score**: These values give a more detailed view of the model's performance:

  (The Logistic Regression Model gives Precision as 100% due to the use of synthetic data, Recall is 86.67% and F1-Score is 92.86%)

2. Confusion Matrix

The values are for the Obsessive-Compulsive Disorder (OCD) dataset:

- *10 True Negatives*
- *0 False Positives*
- *2 False Negatives*
- *13 True Positives)*

3. Data Visualization

- **Receiver Operating Characteristic** (ROC) and **Precision-Recall Curve**

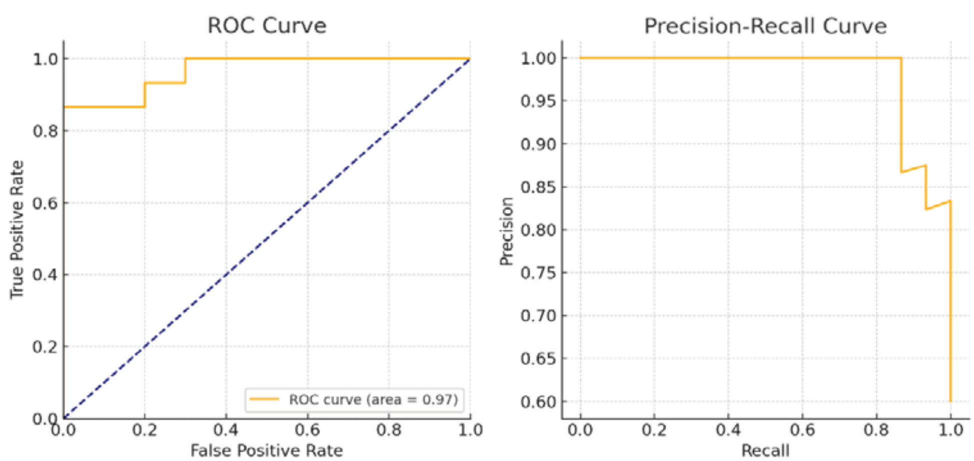

Figure 2. ROC and Precision-Recall Curve.

4. Final Botpress Workflow Integration Results

After testing and evaluating the logistic regression model, the findings were combined into Botpress for user interaction and prediction. The following are the results obtained:

- It received all user inputs related to every disease (age, family medical history, appetite status, and other relevant parameters) and processed them to predict the probability of developing each disease with the trained model.
- The workflow correctly predicted the diseases for end-users, which is then later checked for correctness by cross-validation against the test data.
- Users get further options where they are given an appointment booking or a hospital recommendation near them if the model predicts that they are likely to contract a disease.

Discussion:

Interpretation of the Results to the Research Question or Hypothesis

1. The integration of logistic regression with the LLaMA 3 transformer model enhances disease prediction, demonstrating strong predictive power for four mental illnesses and enabling intuitive access to complex health information through a conversational interface.

2. This approach not only delivers personalized disease risk predictions but also promotes proactive healthcare management and improves doctor-patient interactions through detailed reports from patient queries.

Comparison of Findings with Previous Research

This study advances the field by integrating logistic regression with transformer models to enhance interpretability and usability in predictive analytics, providing robust healthcare solutions that effectively communicate complex data to both patients and healthcare providers.

Explanation of Implications of the Results

The integration of hybrid AI models provides patients with real-time health insights through an accessible chatbot interface, while healthcare providers benefit from structured reports that enhance consultation efficiency and reduce diagnostic errors, ultimately improving treatment outcomes and easing the burden on healthcare systems.

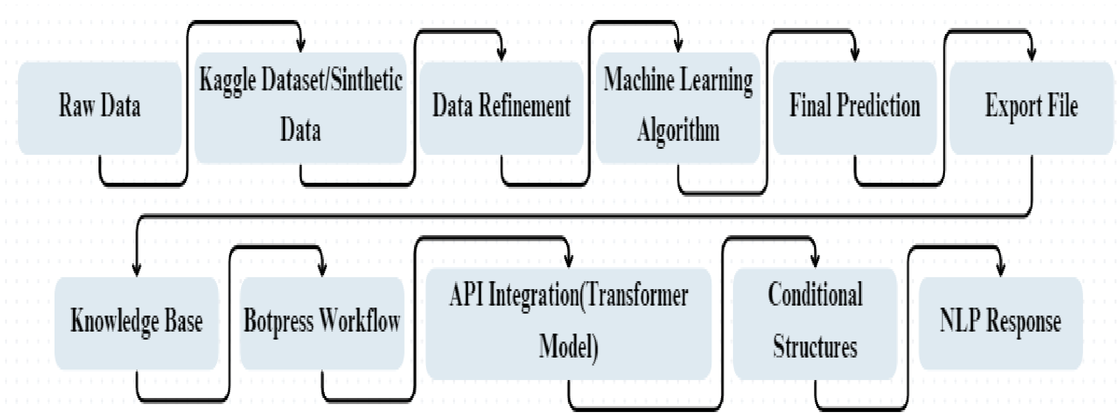

Figure 3. Workflow of Hybrid architecture.

The opportunity to combine traditional machine learning models with transformer-based language models opens a real possibility framework for producing intelligent, conversational health tools that could be stretched out across a very wide ambit of healthcare domains-remote monitoring and surveillance, telemedicine, and treatment planning.

Performance Evaluation: Comparison of the Hybrid Model (Logistic Regression + Transformer) with Standalone Traditional Models

Accuracy, Average Response Time(Seconds), and User Experience

Table 1. Accuracy, Average Response Time(Seconds), and User Experience.

Model	Accuracy(Disease Prediction)	Average Response Time(Seconds)
Logistic Regression Only	85%	0.25s
Transformer Model Only	82%	1.2s
Hybrid Model	91%	1.5s

Criterion	Logistic Regression Only	Transformer Model Only	Hybrid Model
Clarity of Information	3.2	4.5	4.8
Engagement	2.9	4.3	4.7
Trust and Confidence	3.5	4.6	4.9

Limitations of the Study and Suggestions for Future Research

1. The study's promising results are limited by the use of synthetic data, which does not capture real-world healthcare complexities; future research should focus on real datasets and address ethical concerns regarding data privacy and consent.

2. While the chatbot shows advanced conversational capabilities, it requires further fine-tuning and integration of expert knowledge to handle complex medical questions; future work should enhance its accuracy, explore chronic disease analytics, and prioritize real-world deployment and EHR integration.

Conclusion:

1. **Summary of the Key Findings**

   Combining logistic regression with advanced transformers like LLaMA 3 enhances disease prediction accuracy and usability in healthcare, integrating structured data processing with interpretive power and providing intuitive, timely insights for non-technical users, despite a slight increase in response time.

2. **Importance of the Findings in the Broader Context**

   It finally comes down to the need for smart and accessible healthcare tools that add value to predictions and patient engagement through language-based conversational interfaces that translate complex data into actionable insight. This model supports telemedicine by providing real-time health management for patients and releasing the burden from the providers, thus broadly making AI-driven solutions applicable to nonspecialists.

3. **Suggestions for Practical Applications or Policy Implications**

This study highlights the feasibility of hybrid AI models in preventive healthcare using mobile health applications for patients with diseases like depression and OCD while making diagnoses sooner with reports from AI. Policymakers should enable its integration with telemedicine for more accurate and, in real-time, predictions as well as by waiving the data privacy issues. It also shows how the unification of traditional machine learning and advanced transformers constructs effective, user-friendly healthcare predictive tools for both patients and providers.

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Conflict of Interest:

The authors declare that they have no known conflicts of interest associated with this research, and there has been no significant financial support that could have influenced its outcomes.

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