Transparency in Medical Recommendations: A Comprehensive Methodology of Explainable AI Techniques in Healthcare

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ABSTRACT
Explainable AI (XAI) techniques are increasingly crucial in healthcare for enhancing transparency and trust in medical recommendations. XAI refers to methodologies and tools that make the decision-making process of AI systems transparent and comprehensible to humans. This paper reviews and proposes a comprehensive methodology to improve the explainability and trustworthiness of healthcare recommender systems. Key components include advanced machine learning models, such as Convolutional Neural Networks and Restricted Boltzmann Machines, integrated with explainable AI techniques like LIME and SHAP. The system incorporates collaborative, content-based, and graph-based filtering for personalized recommendations, supported by robust UI/UX design principles. The methodology aims to bridge the gap between AI-driven recommendations and user trust, thereby enhancing patient outcomes and healthcare delivery efficiency.

Keywords: Explainable AI (XAI), healthcare recommender systems, transparency, trust, EHR, LIME, SHAP, medical decision-making.

1. INTRODUCTION

The integration of artificial intelligence (AI) technology has brought about a dramatic revolution in the healthcare industry in recent years. Recommender systems are one of the most important of these; they help with patient care management, diagnosis, and personalized medical treatments. AI-powered recommender systems are designed to offer tailored recommendations by sifting through massive datasets to find trends and preferences. However, despite their potential, the adoption of AI and recommender systems in healthcare is met with significant challenges, primarily centred around transparency and explainability [1, 2, 3]. This research paper aims to provide a comprehensive review of Explainable AI (XAI) techniques in the context of medical recommender systems [4, 5]. The complexity and opacity of AI models, often described as "black boxes," pose a critical barrier to their acceptance among healthcare professionals and patients. It is essential for medical practitioners to understand the rationale behind AI-generated recommendations to trust these systems [6]. This review encompasses various approaches to XAI in healthcare, including graph- based methods [5], hybrid distributional models [3], and ensemble techniques [4], with a focus on addressing crucial challenges such as privacy, interpretability, and user confidence in AI-powered healthcare systems. They can suggest potential diagnoses based on patient symptoms, recommend treatment plans tailored to individual patient histories, and even identify the most suitable clinical trials for patients [7, 8]. By elucidating how XAI can be integrated into healthcare recommender systems, this study seeks to bridge the gap between AI technology and its practical application in medical settings [9]. Content-based filtering, collaborative filtering, and hybrid models are the three main categories into which these systems fall [10]. By analysing vast amounts of medical data, these systems can support healthcare providers in making more informed and efficient decisions, ultimately improving patient outcomes and operational efficiency [11, 12]. While content-based filtering focuses on item features to suggest related items, collaborative filtering uses the experiences and tastes of similar users to produce suggestions. Hybrid models combine both approaches to improve accuracy and reliability [13].

2. LITERATURE SURVEY

Explainable AI in healthcare has seen significant advancements in recent years, with numerous studies exploring various aspects of this field. Nazar et al. [1] examined the intersection of Human-Computer Interaction and XAI in healthcare, emphasizing the need for more research and XAI's potential to enhance user confidence and system transparency. Srinivasu et al. [2] investigated the transition from black box models to explainable AI in healthcare, while Albahri et al. [3] conducted a comprehensive systematic review of trustworthy and explainable AI in healthcare, providing valuable insights into the current state of the field and hybrid distributional models combining sparse graph-based representations with dense vector representations. Several innovative approaches have been developed to address specific challenges in healthcare AI. Saraswat et al. [4] proposed novel architectures for CT image classification and segmentation. These include sophisticated EXAI ensemble techniques for CT image classification and ECG monitoring. Sangaiah et al. [5] created explainable medical recommendation systems using graph principles and community detection techniques and graph-based approaches for medical recommendations. Liu et al. [7] developed multifunctional healthcare recommendation systems based on knowledge graphs and deep neural networks in 5G networks. Sahoo et al. [9] addressed privacy concerns in healthcare recommender systems using multi-party computing to secure patient data during the recommendation process. Trattner et al. [10] discussed common recommendation strategies used in healthcare, such as collaborative filtering, content-based filtering, and knowledge-based recommendation. These strategies are applied in various domains, including food, nutrition, medicine, and physical activity recommendations. Specific models have been developed to address particular healthcare challenges.

Ihnaini et al. [11] proposed the Smart Healthcare Recommendation System for Multidisciplinary Diabetes Patients (SHRS-M3DP), achieving impressive accuracy rates. Afolabi et al. [12] introduced the Real-Time Recommendations Sharing Community for Aged and Chronically Ill People in Connected Health (ReTReSCAP- CH), focusing on data aggregation and sharing among partners for effective care delivery. Chinnasamy et al. [13] presented deep learning-based collaborative filtering approaches, combining Restricted Boltzmann Machines (RBM) and Convolutional Neural Networks (CNN), showing promising results in healthcare recommendations. The reviewed papers showcase a diverse set of XAI approaches for healthcare applications. Kulev et al. [14] proposed algorithmic models for identifying preventive actions based on correlations between users' health statuses and physical activity levels. Health Recommender Systems (HRS) have been extensively studied, with researchers [15-17] examining various aspects including types, user interfaces, algorithms, and applications. These solutions address crucial challenges such as privacy, interpretability, and user confidence in AI- powered healthcare systems. Aditya et al. [20] proposed a unique solution for unmasking AI-generated texts through XAI intelligence and they implemented a LIME & SHAP based methodology to explain the features that play an important role in detecting whether the text was generated by AI or not. Existing methodologies have made significant progress in developing explainable and trustworthy AI systems for healthcare. Nilesh et al. [21] how XAI pipelines are integrated with machine learning and deep learning models to explain the results given by these models.

However, there is still room for improvement and innovation in proposed methodologies. methods for analysing temporal patterns in patient data and identifying potential causal relationships could improve the quality of recommendations and explanations. Emphasizing user-centred design in XAI development is crucial to ensure that the explanations provided are not only accurate but also meaningful and actionable for healthcare professionals and patients. Ethical considerations should be at the forefront of AI integration in healthcare. Developing frameworks for continuously monitoring and mitigating biases in AI models is essential to ensure fair and equitable recommendations across diverse patient populations. Finally, fostering interdisciplinary collaboration between AI researchers, healthcare professionals, and domain experts will ensure that the developed XAI systems address real-world clinical needs and challenges. This holistic approach will not only improve the technical aspects of healthcare but also enhance its practical implementation and acceptance in clinical settings.

3. PROPOSED METHODOLOGY

Based on the research that we have performed, here is a comprehensive proposal of a methodology that helps to improve the explainability, trust and transparency of a recommender system in Healthcare. Furthermore, the system assesses several health characteristics to make personalized recommendations to the client. Throughout the process, several "Explain why?" steps are incorporated to emphasize transparency and explainability. These processes guarantee that users understand the reasoning behind each recommendation, which increases trust and engagement.

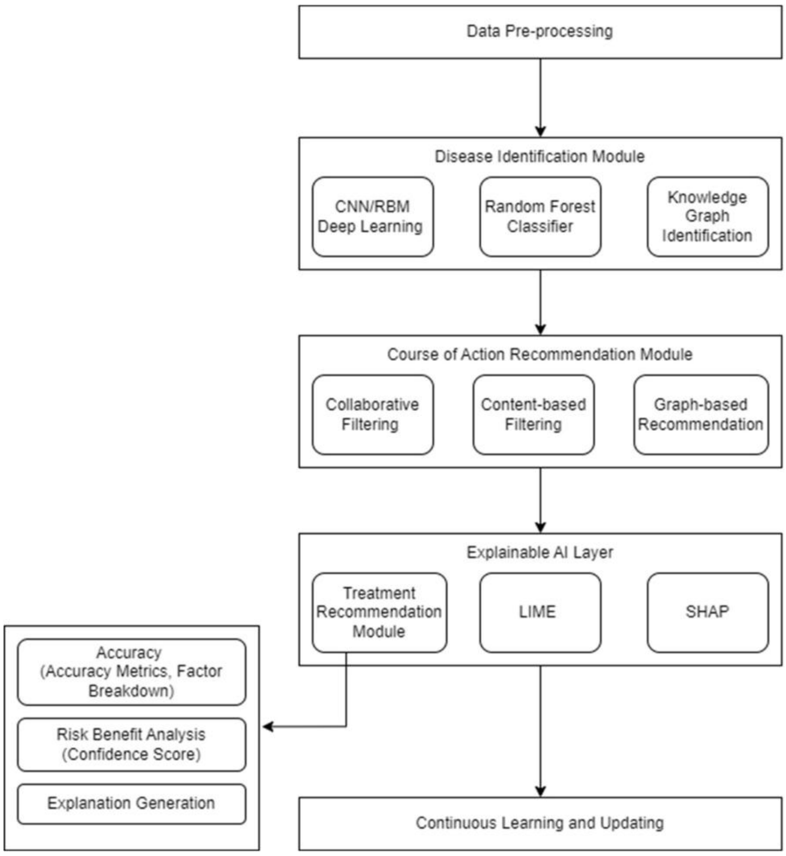

Figure 1:Detailed Technical Architecture of the Symptom-Based Disease Identification System

1. Data Pre-processing

The datasets used contained parameters to detect types of diseases and also corresponding precautionary measures. The preprocessing began by examining for any inconsistencies followed with extracting and cleaning symptoms from the dataset, resulting in a unique list of symptoms. This structured approach ensured that the data was properly formatted and ready for machine learning model development.

2. Disease Identification Module

The disease identification module combines advanced machine learning techniques with structured medical knowledge to provide accurate diagnoses and clear explanations. At its core is a deep learning model, either a Convolutional Neural Network (CNN), Restricted Boltzmann Machine (RBM) or Random Forest Classifier, which processes patient data including symptoms, medical history, lab results, and imaging data. This model is trained on a large dataset of pre-diagnosed cases to identify patterns associated with various diseases.

Convolutional Neural Networks (CNN):

The convolution operation is defined as:

$(F*g)(x) = \sum[f(i) * g(x - i)]$ ... (I)

Where F is the input, g is the kernel, and * denotes convolution.

Key Steps:

- Convolution: Apply filters to input data to create feature maps
- Activation: Apply non-linear activation function (e.g., ReLU)
- Pooling: Reduce spatial dimensions of feature maps
- Fully Connected Layers: Flatten and connect to dense layers
- Output: Final classification or regression output

Random Forest Classifier:

Random Forest classifier shines especially when it comes to analysing structured data like patient demographics, symptoms, medical history, and lab results. By combining the insights of multiple decision trees, this approach boosts the accuracy and reliability of the diagnostic process.

Key Steps:

- Decision Trees: Each decision tree acts as a small expert, analysing different slices of patient data to identify disease patterns.
- Bagging (Bootstrap Aggregating): Random Forest trains each tree on different data subsets to enhance diversity and prevent overfitting.
- Majority Voting: The final diagnosis is determined by the most popular prediction among all the decision trees.

Restricted Boltzmann Machines (RBM):
The energy function of an RBM is defined as:
$E(v, h) = -\sum(i,j) v_i * h_j * w_{ij} - \sum i b_i * v_i - \sum j c_j * h_j \quad \ldots (II)$
Where v and h represent the visible and hidden units, respectively, w denotes the weights, and b and c are the biases. The indices i and j refer to the respective positions within the matrices.
Key Steps:

- Initialize weights and biases randomly
- Forward pass: Compute probabilities of hidden units
- Backward pass: Compute probabilities of visible units
- Update weights and biases using contrastive divergence
- Repeat steps b-d for specified number of epochs

The above deep learning model is integrated with a comprehensive medical knowledge graph encompassing diseases, symptoms, risk factors, and treatments, which validates the deep learning model's output and provides additional context. In cases of uncertainty, the system clearly communicates this and encourages professional consultation. The module includes a feedback loop for continuous learning and updating, ensuring it remains current with the latest medical research. Ethical considerations are built into the design, with clear guidelines on the system's role in assisting, not replacing, healthcare professionals.

3. Course of Action Recommendation Module:
Collaborative Filtering for Patient Grouping:
Using this method, patients with comparable health profiles, habits, or treatment results are found.It looks for correlations by analysing patterns in a huge patient database. Based on commonalities in their medical histories, symptoms, therapies, and results, patients are grouped together.A patient's recommendations may come from interventions or therapies that have worked well for patients in their group who are comparable to them.

Content-based Filtering for Patient-Recommendation Matching:
This approach emphasizes the unique qualities and medical background of each patient.
Each patient is given a comprehensive profile that includes information on their lifestyle, prescriptions, medical issues, and demographics. Next, recommendations are produced by comparing the patient's profile to relevant interventions, therapies, or medical guidance. This guarantees that the advice is tailored to the individual patient's health needs and circumstances.

Graph-based Recommendation System:
With this method, conditions, treatments, patients, and results are represented as nodes in an intricate network. In the graph, the relationships between these entities are shown as edges.This graph can be traversed by the system to identify pathways linking a patient's condition to possible cures or results. More intricate, multi-step reasoning can be used to generate suggestions using this method. By displaying the line of reasoning across the graph, it can offer suggestions that are easy to understand.

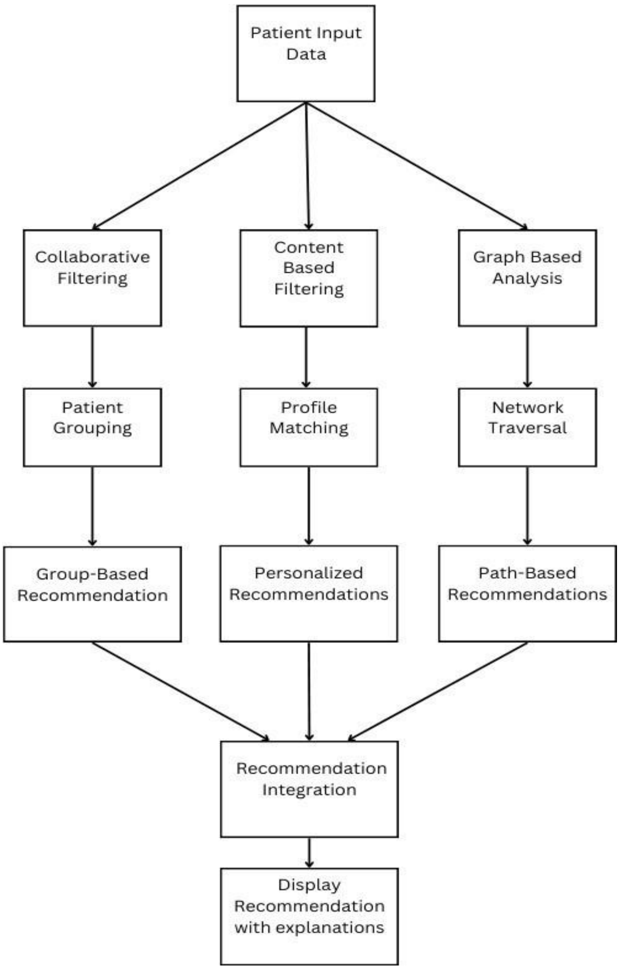

Figure 2: Workflow of Course Of Action Recommendation Module

4. Explainable AI Layer

4.1. Explainable AI Layer in Disease Identification Module

Explainable AI techniques, specifically LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations), are applied for disease identification to reveal the extent of influence factors of each diagnosis. The system generates natural language explanations combining insights from all components, presenting them in a user-friendly format. A confidence score is implemented, considering the model's probability output, knowledge graph match, and explanation consistency. Figure 3 shows how Explainable AI models have been incorporated in the previously elaborated identification module.

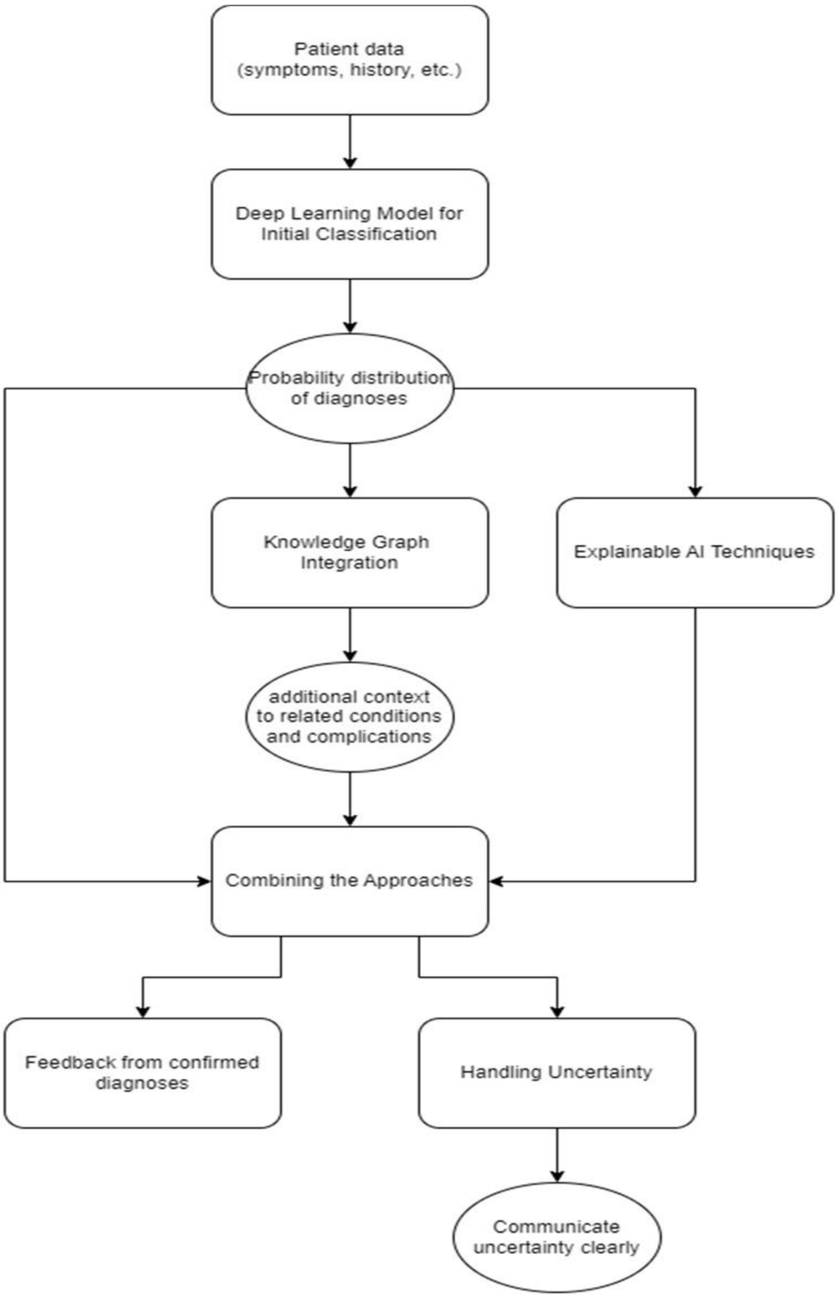

Figure 3: Integrated Work flow of the Disease Identification with Explanation Module

4.2. Explainable AI Layer in Treatment Recommendation Module

The Treatment Recommendation Module leverages advanced XAI techniques to provide personalized medical advice, utilizing key performance metrics to ensure reliability and accuracy. Precision, recall, and the F1 score are crucial in evaluating the model's effectiveness, with precision minimizing false positives, recall ensuring critical health issues aren't overlooked, and the F1 score offering a balanced assessment. Employing ensemble methods that combine multiple models enhances overall accuracy by leveraging diverse predictive strengths. The inclusion of confidence scores for each prediction aids healthcare professionals in prioritizing and making informed decisions, especially in urgent situations. Furthermore, displaying a breakdown of factors contributing to each prediction improves transparency and interpretability, allowing medical experts to understand and verify the AI's reasoning. These metrics and methodologies collectively bolster trust in medical recommendation systems by providing a comprehensive, accurate, and transparent framework for XAI-based predictions, ultimately supporting healthcare providers in delivering more effective and personalized patient care. The factors are as follows:

i. Precision: This metric calculates how many of the positive predictions made by the model are actually correct. In the medical field, this is crucial because it helps minimize false positives— cases where a condition is predicted but doesn't actually exist.
ii. Recall: This quantifies how well the model identifies true positive cases. In healthcare, high recall is must to ensure that significant health issues are not overlooked.
iii. F1 Score: The F1 score provides a balanced assessment of the model's performance by combining precision and recall. This offers a fair overall measure of the model's effectiveness, helping healthcare providers trust its predictions.
iv. Using an Ensemble Method Combining Multiple Models: By leveraging the strengths of different predictive models, this approach enhances overall accuracy. It can include techniques like neural networks, gradient boosting, and random forests, and aggregate predictions using strategies such as voting, averaging, or stacking. Compared to single models, this method often results in more reliable and accurate forecasts.
v. Providing a Confidence Score for Each Prediction: The confidence score reflects the model's certainty about its prediction. This score can be derived from the agreement among models in ensemble methods or from the probabilities in probabilistic models. A higher confidence score indicates a more accurate prediction, aiding healthcare professionals in prioritization and decision-making, especially in urgent situations.
vi. Displaying a Breakdown of Factors Contributing to the Prediction: This involves showing which input features significantly influenced the prediction. A visual representation, like a waterfall chart, can be used to demonstrate how each factor contributes positively or negatively to the outcome. This breakdown improves the model's interpretability, which is vital in healthcare settings, allowing professionals to understand and potentially verify the model's reasoning.

4.3 Mathematical Background of LIME & SHAP

1. Local Interpretable Model-agnostic Explanations (LIME)

Formula: The objective function for LIME is: $argminL(f, g, \pi_x) + \Omega(g)$ ... (III)

Where f is the original model, g is the explanation model, πx is the locality around x, and Ω(g) is the complexity of the explanation.

Key Steps:

a) Select an instance to explain
b) Perturb the input and get predictions from the black-box model
c) Weight the perturbed samples based on their proximity to the original instance
d)Train a simple, interpretable modelon the weighted perturbed samples
e)Extract feature importances from the interpretable model

2. Shapley Additive exPlanations (SHAP)

Formula: The SHAP value for feature i is calculated as:

$\varphi_i = \sum[S \subseteq N\{i\}] (|S|!(n-|S|- 1)!/n!) * [f_x(S \cup \{i\}) - f_x(S)]$ ...(IV)

Where N is set of all features, S is subset of features, and f_x is the prediction function.

Key Steps:

a) Define the set of features and the model to be explained
b) For each feature:

- Generate all possible subsets of features excluding the current feature
- Calculate the marginal contribution of the feature for each subset
- Compute the weighted average of these marginal contributions

c) Aggregate SHAP values for all features
d) Visualize results (e.g., summary plot, force plot)

5. Experimentation And Results

The first datasets used has 132 parameters on which 42 different types of diseases can be predicted. The other dataset is to find the disease by symptoms. It also has additional data that gives you precautionary measures after predicting the disease. The datasets used are cited below as [18] and [19]. The data preprocessing involved applying one-hot encoding to the symptoms data, converting them into a binary feature. This transformed the dataset into a format where each row represents a unique combination of symptoms as binary values, making it suitable for training machine learning models. Disease identification involved training and evaluating machine learning models, primarily a Decision Tree Classifier and a Random Forest Classifier. Both models trained using the features and target labels from the training dataset and then tested on the testing dataset.

```
{'Fungal infection': [{'Disease_ID': 101,
   'Precaution_1': 'bath twice',
   'Precaution_2': 'use detol or neem in bathing water',
   'Precaution_3': 'keep infected area dry',
   'Precaution_4': 'use clean cloths'},
  [{'Medicine_ID': 201,
    'Medicine_Name': 'Antifungal\xa0cream',
    'Medicine_Composition': 'clotrimazole, econazole, ketoconazole, miconazole, tioconazole, terbinafine, and amorolfine',
    'Medicine_Description': 'a pharmaceutical fungicide or fungistatic used to treat and prevent mycosis'},
   {'Medicine_ID': 202,
    'Medicine_Name': 'Antifungal liquids',
    'Medicine_Composition': 'clotrimazole, econazole, ketoconazole, miconazole, tioconazole, terbinafine, and amorolfine',
    'Medicine_Description': 'a pharmaceutical fungicide or fungistatic used to treat and prevent mycosis'},
   {'Medicine_ID': 203,
    'Medicine_Name': 'Antifungal sprays',
    'Medicine_Composition': 'clotrimazole, econazole, ketoconazole, miconazole, tioconazole, terbinafine, and amorolfine',
    'Medicine_Description': 'a pharmaceutical fungicide or fungistatic used to treat and prevent mycosis'}]],
 'Food allergy': [{'Disease_ID': 102,
   'Precaution_1': 'apply calamine',
   'Precaution_2': 'cover area with bandage',
   'Precaution_3': 'use ice to compress itching',
   'Precaution_4': nan},
  [{'Medicine_ID': 204,
    'Medicine_Name': 'Antihistamine',
    'Medicine_Composition': 'Brompheniramine, Cetirizine, Chlorpheniramine',
    'Medicine_Description': 'Antihistamines are drugs which treat allergic rhinitis and other allergies.'}]],
 'GERD': [{'Disease_ID': 103,
   'Precaution_1': 'avoid fatty spicy food',
   'Precaution_2': 'avoid lying down after eating',
   'Precaution_3': 'maintain healthy weight',
   'Precaution_4': 'exercise'},
  [{'Medicine_ID': 205,
    'Medicine_Name': 'antacid',
    'Medicine_Composition': 'calcium carbonate, magnesium hydroxide, aluminum hydroxide and/or sodium bicarbonate',
    'Medicine_Description': 'An antacid is a substance which neutralizes stomach acidity and is used to relieve heartburn'},
   {'Medicine_ID': 206,
    'Medicine_Name': 'Antidiarrhoeal',
    'Medicine_Composition': 'chloroform, methanol, and aqueous extracts of Bidens odorata Cav.',
    'Medicine_Description': 'An anti-diarrhoeal drug is any medication which provides symptomatic relief for diarrhoea'},
   {'Medicine_ID': 207,
    'Medicine_Name': 'Proton-pump inhibitor',
    'Medicine_Composition': 'esomeprazole, lansoprazole, omeprazole, pantoprazole and rabeprazole',
    'Medicine_Description': 'a group of medicines that work on the cells that line the stomach, reducing the production of acid'}]],
 'Chronic cholestasis': [{'Disease_ID': 104,
   'Precaution_1': 'cold baths',
   'Precaution_2': 'anti itch medicine',
   'Precaution_3': 'consult doctor',
   'Precaution_4': 'eat healthy'},
  [{'Medicine_ID': 208,
    'Medicine_Name': 'Ursodeoxycholic acid (UDCA)\n\n',
    'Medicine_Composition': 'ursodeoxycholic acid',
```


Figure 4: Output of Disease identification and Course Of Action Recommendation Modules

The above figure 4 showcases the results of a disease identification module and the course of action recommendations. It displays the predicted disease along with corresponding precautionary measures and recommended medications. The diseases identified include conditions such as fungal infections, food allergies, and GERD. For each disease, specific precautions are provided, like avoiding certain foods or maintaining hygiene. Additionally, relevant medications are suggested, such as antifungal creams or antacids, tailored to treat the identified conditions effectively.

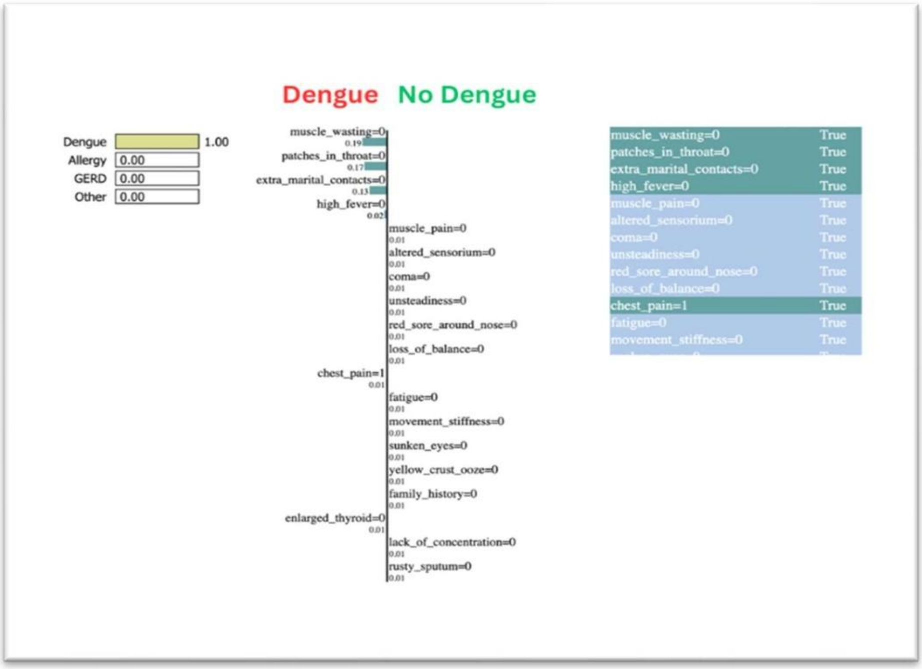

Figure 5: LIME for Dengue

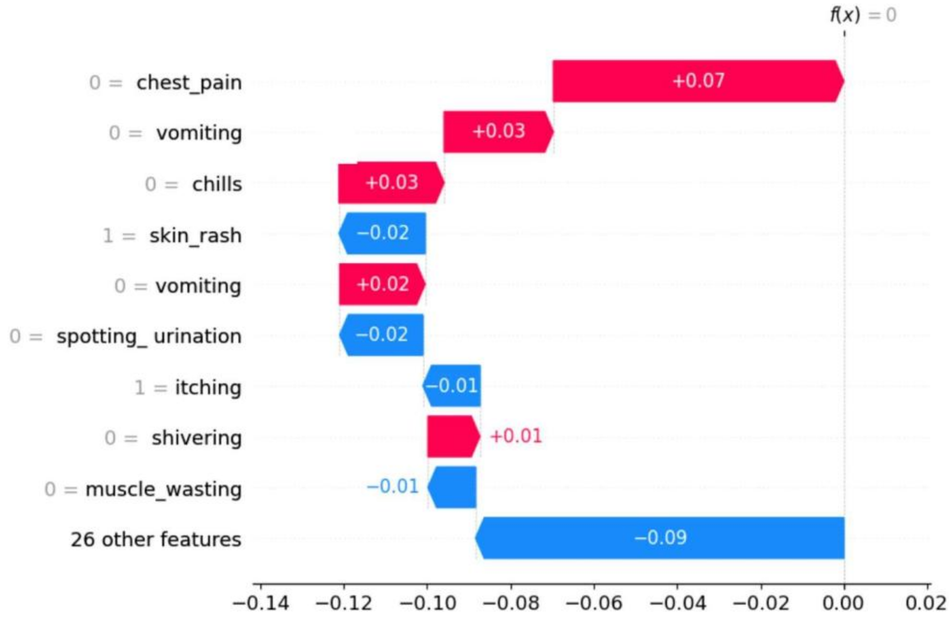

Figure 6: SHAP for Dengue

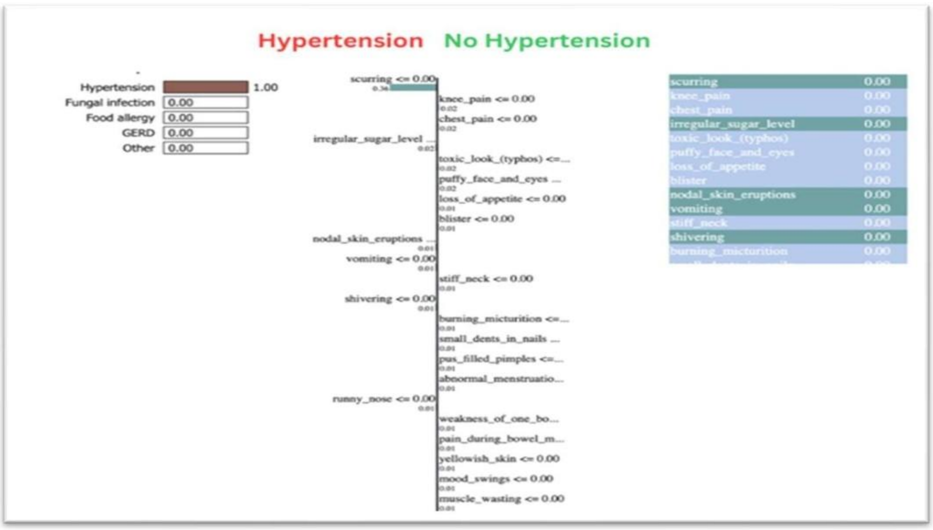

Figure 7: LIME for Hypertension

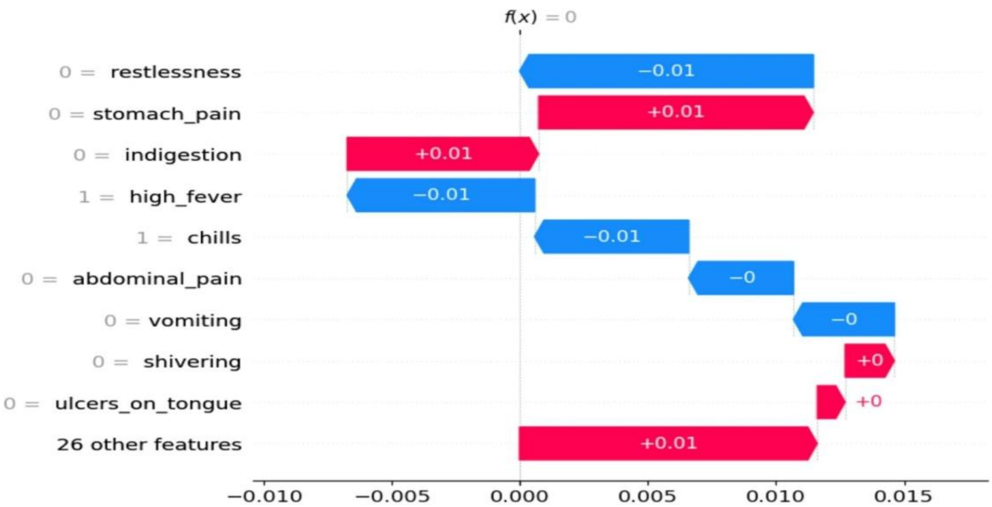

Figure 8:SHAP for Hypertension

LIME and SHAP were implemented on the dataset to determine which features played an important role in classifying the diseases using the models (decision tree and random forest). This feature importance and identification then helps in order identify which features related to disease classification contribute the most prominently.The two LIME graphs Figure 5 and 7 are for two different disease data points. First, dengue shows that features like chest pain, high fever and muscle wasting played an important role in classifying the datapoint as dengue. Second, Hypertension shows that features like scurring, irregular sugar levels, nodal skin eruptions and shivering contribute to classifying that datapoint as Hypertension.Variable Importance Plot for migraine shows which features played a prominent role for its classification. Features like headache, chills, anxiety and mood swings played an important role for classifying that datapoint as migraine. Chills are a significant symptom in diagnosing various diseases. This symptom, characterized by sudden and intense shivering, often indicates the body's response to infection. In diseases like malaria and dengue, chills frequently accompany high fevers, signalling the immune system's effort to combat the pathogens. Similarly, in influenza, chills are a common early sign, often preceding a spike in body temperature. Recognizing chills as a symptom can thus be crucial for the early detection and differentiation of these illnesses, enabling timely and appropriate medical intervention. Chest pain is a critical symptom that can indicate a range of serious health conditions, making its recognition important in medical diagnosis. It is often associated with heart-related issues, such as heart attack, where the pain may radiate to the arms, neck, or back. However, chest pain is not exclusive to cardiac problems; it can also signify respiratory issues like pneumonia or pulmonary embolism, where the pain may worsen with deep breaths.

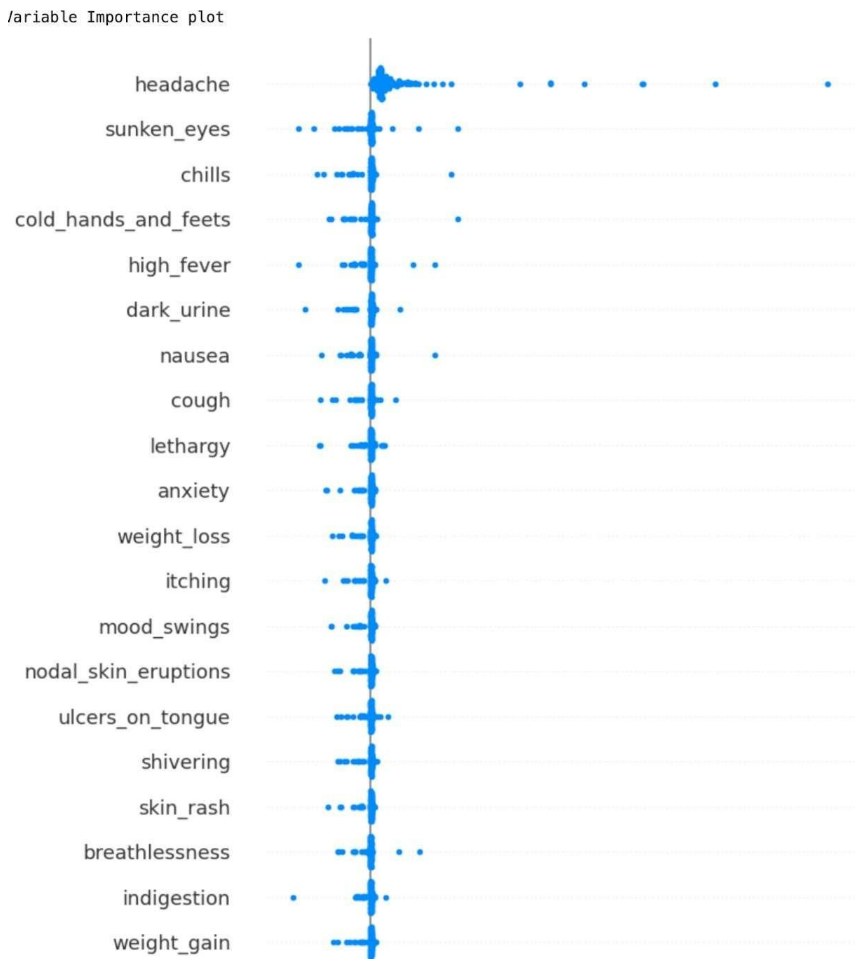

Figure 9: Variable Importance Plot for migraine

A headache is a common and adaptable symptom that can be linked to a variety of illnesses, from minor to serious. It is a defining feature of neurological conditions such as migraines, in which the pain is frequently severe and localized, occasionally accompanied by nausea and visual problems. Furthermore, tension headaches are associated with musculoskeletal problems or stress, whereas severe, abruptly occurring headaches may be a sign of more dangerous illnesses such as meningitis or a brain aneurysm. A complete medical evaluation should be performed to determine and treat the underlying cause of a headache, especially if it is atypical in terms of intensity, duration, or associated symptoms, given the wide range of possible causes.

6. CONCLUSION

In the domain of healthcare, the integration of Explainable AI techniques holds significant promise for enhancing the transparency, trustworthiness, and efficacy of medical recommender systems. This paper has proposed a robust methodology aimed at addressing critical challenges in contemporary healthcare practices, focusing on improving the interpretability of AI-driven recommendations and ensuring patient-centric outcomes. Key to this methodology is the deployment of advanced machine learning models, such as Convolutional Neural Networks (CNNs) and Restricted Boltzmann Machines (RBMs), tailored for processing intricate medical data. These models are complemented by cutting-edge XAI methods like Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP), enabling the system to provide accurate diagnoses and treatment suggestions while offering clear, comprehensible rationales for each decision. This transparency not only empowers healthcare providers to make informed decisions but also engages patients in their care, fostering a collaborative healthcare approach. Moreover, this methodology incorporates diverse recommendation strategies—collaborative filtering, content-based filtering, and graph- based recommendation systems—ensuring personalized recommendations aligned with individual patient profiles and healthcare needs. This personalized approach is crucial for improving patient adherence and overall health outcomes, thereby enhancing the efficacy of healthcare delivery. The user interface and experience design of this system play a pivotal role in building trust and usability. Grounded in Human-Computer Interaction (HCI) principles, this interface features intuitive design elements such as "Explain This" functionalities and visual representations of decision-making processes, enhancing user understanding and confidence in AI-driven recommendations. Privacy preservation is paramount in healthcare recommender systems (HRS), and this methodology addresses this concern through innovative techniques such as Multi-Party Computing (MPC) and Federated Learning. These methods facilitate collaborative data analysis while ensuring strict adherence to patient confidentiality and regulatory standards like GDPR and HIPAA. Looking forward, the future applications of XAI in healthcare are promising, with potential advancements in AI-powered smart devices for real-time health monitoring and outbreak management. By bridging the gap between AI insights and human understanding, this methodology aims to elevate healthcare standards, empower stakeholders, and improve global health outcomes. In conclusion, this research underscores the transformative potential of XAI in healthcare, paving the way for more transparent, effective, and patient-centred medical practices. Through ongoing innovation and collaboration, this study envision a future where AI enhances healthcare professionals' capabilities and ensures equitable access to quality healthcare worldwide.

7.Future Scope

Future applications of Explainable AI in healthcare are poised to transform illness management and tailored medicine. One interesting avenue is the creation of AI-powered smart devices capable of extensive symptom analysis and health parameter monitoring. These devices could possibly detect ailments and offer therapies in the absence of medical personnel, while also providing clear explanations for their suggestions. This transparency would increase patient trust and enable informed decision-making. Furthermore, XAI approaches could be applied to large-scale medical outbreak identification and management. AI systems could detect probable epidemics or pandemics early on by evaluating symptom frequency and geographical distribution patterns. Hence XAI can revolutionize healthcare and public health interventions.

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