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Lumina: Bridging Healthcare Knowledge Gaps Through AI-Powered Assistance

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Abstract:
Background: Healthcare systems are increasingly incorporating artificial intelligence to address diverse medical needs, including improving access to healthcare resources and aiding non-medical individuals in understanding complex medical information. One such innovation is Lumina, a healthcare chatbot designed to provide personalised medical assistance, leveraging advanced AI technologies. Lumina aims to simplify medical processes such as wound detection, prescription analysis, and health insurance advisory through an integrated and user-friendly interface. Additionally, AI-powered psychometric analysis systems can assess an individual's stress levels and predict mental states by analyzing responses to dynamically generated questions, categorizing them into states like stable, depressive, impulsive, or anxious. These systems utilize sentiment analysis and logistic regression to provide personalized recommendations, enhancing mental health support and coping strategies.
Methods: Lumina integrates advanced technologies to provide comprehensive healthcare services. For general medical inquiries, it utilizes OpenAI's natural language processing models to deliver reliable responses, enhanced with audio and video outputs for improved accessibility. The wound detection feature is powered by a Convolutional Neural Network (CNN), enabling accurate classification of wound types from uploaded images and offering tailored first-aid i.joshirescription analysis feature employs the Google Vision API and SERP API to extract and validate prescription details, ensuring medication accuracy. To enhance user interaction and mental health support, Lumina incorporates SBERT (Sentence-BERT) for intelligent filtering of similar questions, DistilBERT for sentiment analysis of user responses, a Random Forest Classifier to predict stress levels (Low, Moderate, High), and the Gemini API to generate personalized AI-based stress reports.
Results:
- Wound Detection: 69% accuracy, 71% F1 Score, 35 ms inference time (MobileNetV2).
- HIF Advisor: 92.3% parsing accuracy, 91.8% completeness (Gemini Pro Flash API).
- Prescription Analysis: 89.7% OCR accuracy, safe dosage verification (Azure OCR).
- Sentiment Analysis: Utilizes DistilBERT, which achieves an accuracy of 91.3% on the SST-2 dataset, to assess user responses.
- Stress Level Prediction: Achieves 86.96% accuracy in classifying stress levels (Low, Moderate, High) using a Random Forest Classifier, enabling proactive mental health support

Conclusion: Lumina integrates AI to provide healthcare solutions across multiple modules. Further validation is needed to ensure its effectiveness.

Keywords: Healthcare Chatbot; AI in Healthcare, Wound Detection,Prescription Analysis, Health Insurance Advisor, Psychometric Assistant, Lumina

I. INTRODUCTION

Healthcare is a cornerstone of human development, playing a critical role in enhancing the quality of life, productivity, and longevity. It encompasses a wide spectrum of services and technologies designed to promote, maintain, and restore health. From primary care to advanced research, healthcare systems are equipped to address diverse medical needs. However, despite its significance, many individuals—particularly those outside the medical profession—face challenges in accessing, understanding, and effectively utilizing healthcare resources due to a lack of knowledge.

A. The Evolution of Healthcare

Over centuries, healthcare has transitioned from rudimentary practices to a sophisticated field driven by scientific advancements and technology. Modern healthcare systems leverage cutting-edge innovations such as artificial intelligence (AI), robotics, telemedicine, and personalized medicine to improve diagnostic accuracy, treatment efficacy, and patient outcomes. These advancements have also increased access to quality care while striving to reduce costs.

B. Key Components of Healthcare

Healthcare is a multifaceted domain broadly divided into several core components:

1. **Primary Care:** The first level of healthcare addressing general health needs, prevention, and wellness.
2. **Specialized Care:** Focused treatments provided by experts for complex conditions in secondary and tertiary care facilities.
3. **Public Health:** Strategies aimed at disease prevention and health promotion at the community level.
4. **Health Informatics**: The integration of technology and data to streamline processes and enhance patient care.

C. Challenges Faced by Non-Medical Individuals

For non-medical individuals, navigating the healthcare system can be daunting due to several challenges:

1. **Understanding Medical Terminology:** Complex jargon and abbreviations often create barriers to comprehension.
2. **Interpreting Medical Information:** Difficulty in understanding prescriptions, test results, or diagnoses may lead to confusion and anxiety.
3. **Recognizing Symptoms:** A lack of basic medical knowledge can delay recognition of critical symptoms and necessary medical attention.
4. **Access to Resources:** Limited knowledge about available healthcare services and systems can hinder timely access to care.
5. **Trust and Decision-Making:** Misunderstanding medical advice can erode trust in healthcare professionals, complicating decision-making processes.

D. Essential Concepts for Beginners in Healthcare

To bridge the gap in understanding, non-medical individuals must develop foundational knowledge in the following areas:

1. **Human Anatomy and Physiology:** Basic understanding of body structure and function.
2. **Common Diseases and Symptoms:** Familiarity with prevalent health conditions and their signs.
3. **First Aid and Basic Care:** Knowledge of immediate care practices for injuries and common emergencies.

4. **Health Literacy:** Ability to understand and act upon medical information provided by professionals.

E. The Role of Technology in Simplifying Healthcare

Technological advancements are increasingly democratising access to healthcare knowledge. Tools like AI-powered chatbots, mobile health apps, and wearable devices empower individuals to monitor their health, seek advice, and manage conditions. For instance, AI chatbots can answer medical queries in simple language, while telemedicine platforms allow users to consult doctors remotely, eliminating geographic and logistical barriers.

F. Challenges in the Healthcare Ecosystem

Despite its evolution, the healthcare sector faces persistent challenges:

1. **Inequitable Access:** Disparities in access to quality care remain a global issue.
2. **Rising Costs:** The financial burden of healthcare services is a significant barrier for many.
3. **Global Health Threats:** Pandemics, antimicrobial resistance, and non-communicable diseases pose ongoing risks.
4. **Digital Divide:** Unequal access to technology can limit the benefits of digital health innovations for marginalized communities.
5. **Data Privacy and Security:** Safeguarding sensitive medical information is a critical concern in the digital age.

G. The Importance of Research and Education

Bridging the knowledge gap between medical professionals and the general public requires education and innovative solutions. Simplified resources, accessible Healthcare technologies and widespread health literacy campaigns can empower individuals to make informed decisions about their health. Interdisciplinary collaboration among healthcare providers, technologists, and educators is crucial to creating a system that is inclusive and patient-centered.

II. LITERATURE SURVEY

A. Related Works

In recent years, artificial intelligence and machine learning have been increasingly leveraged in healthcare to enhance diagnostic accuracy, streamline medical processes, and make healthcare accessible to non-medical individuals. Several studies have explored AI-based solutions for various healthcare applications, setting the foundation for the development of Lumina, a comprehensive healthcare assistant.

In 2020, Sharma et al. [1] developed a chatbot for answering medical queries using natural language processing (NLP). The system could provide accurate responses to predefined questions but struggled with complex queries due to limited datasets. In 2021, Zhang et al. [2] introduced a CNN-based image analysis model for wound detection. This model achieved high accuracy in detecting wound severity but required extensive preprocessing of input images. Similarly, in 2022, Park et al. [3] proposed a prescription analysis system utilizing OCR (Optical Character Recognition) combined with machine learning. Although effective, the system faced challenges in handling poorly handwritten prescriptions.

In 2023, Ahmed et al. [4] explored the use of AI to analyze health insurance documents, leveraging NLP and decision-tree-based algorithms to provide policy suggestions. While the model demonstrated strong performance in structured datasets, it struggled with complex, unstructured data. In the same year, Lee et al. [5] implemented an AI-driven telemedicine assistant that integrated multiple APIs for real-time consultations. The system faced limitations in providing region-specific healthcare advice due to a lack of localized data.

These studies highlight the potential of AI to revolutionize healthcare while also underscoring the need for integrated systems capable of addressing diverse user requirements with minimal technical limitations.

B. Problem Statement

The healthcare domain faces several challenges that prevent effective access and utilization of medical resources by non-medical individuals. These challenges include:

- **Understanding Complex Medical Information**: Medical prescriptions, diagnoses, and insurance policies are often difficult for non-medical users to comprehend, leading to confusion and errors.
- **Integration of Technologies**: While AI models exist for specific tasks like wound detection or insurance advisory, there is a lack of comprehensive systems that integrate multiple functionalities into a single, user-friendly platform.

Table 1: Key Challenges

Key Challenges	Description
Absence of original medication	Most of the time original medication cannot be available in the pharmacy where we require medical assistance for getting the substitutes.
Medical Image Analyser	Detecting conditions like diabetic foot ulcers, pressure sores, and other wounds is challenging without high-resolution imaging and proper tools. Advanced MRI scans further aid in diagnosing internal abnormalities for accurate treatment.
Medical Prescription Understanding	Users may misinterpret prescriptions, such as "Metformin 500 mg" or "Salbutamol Inhaler," leading to medication errors or incorrect usage.
AI-Enhanced Psychometric Assessments	Traditional fixed-question psychometric tests can be limited. Integrating AI allows for dynamic question adjustments based on user responses, enhancing the accuracy of mental health evaluations.
Health Insurance Policy Complexity	Insurance terms like "deductibles" or "copays" can be confusing, making it hard to understand coverage details and medication plans.

III. PROPOSED SYSTEM

A. Overview

The proposed system, **Lumina**, is a comprehensive AI-powered healthcare assistant designed to address the limitations of existing solutions in the healthcare domain. Lumina integrates advanced artificial intelligence, machine learning, and natural language processing (NLP) technologies to deliver a unified platform capable of assisting users with medical queries, wound detection, prescription analysis, and health insurance advisory. By combining multiple functionalities into a single user-friendly interface, Lumina aims to make healthcare more accessible, accurate, and efficient.

B. System Features

The key components of the proposed system include:

1. **Medical Prescription Analysis:**
   - Combines Optical Character Recognition (OCR) and machine learning techniques to extract and validate prescription details.
   - Offers dosage instructions, medication purposes, and alerts for potential drug interactions.
   - Handles handwritten and printed prescriptions with high accuracy.
2. **Medical Image Analyzer (Wound & Medical Reports)**
   - Analyzes wound images to assess severity, type, and provide first-aid recommendations.
   - Users can upload images of MRI scans, blood test reports, or other medical documents. The system applies bounding box detection to highlight key areas and provides a brief summary of the findings.
   - Integrated Roboflow pre-trained models along with custom-trained models for anomaly detection in MRI scans.
3. **Health Insurance Advisory:**
   - Processes structured and unstructured insurance data using Gemini Pro Flash API to provide personalized policy suggestions.
   - Clarifies complex terms like "deductibles" and "co-pays," making policies easier to understand.
4. **AI-Enhanced Psychometric Assessments:**

- Dynamic Questionnaire Generation: Utilizes AI algorithms to create personalized question sets in real-time, adapting to user responses for a tailored assessment experience.
- Sentiment Analysis Integration: Employs tools like VADER to analyze the emotional tone of user inputs, enhancing the accuracy of stress and mental state evaluations.
- Stress Level Classification: Applies machine learning models, such as logistic regression, to categorize stress levels (low, medium, high) based on analyzed data, facilitating proactive mental health support.

C. Innovations and Advantages

The Lumina system stands out from existing solutions due to the following innovations:

- **Integration:** Combines multiple healthcare functionalities into a single platform, reducing the need for separate applications.
- **Accessibility:** Prioritizes user experience with intuitive design and support for underserved populations.
- **Reduce Lack of Knowledge:** It is suitable for people who have no prior knowledge of medicine or a related field.

D. Benefits

- Empowers non-medical individuals with easy-to-use tools for managing healthcare tasks.

- Reduces errors in interpreting prescriptions or health insurance documents.
- Enhances early detection of wound-related complications, minimizing the need for advanced interventions.
- Bridges the gap in healthcare accessibility for remote or underserved regions.

E. System Architecture

- The system comprises a front-end interface (web and mobile), a back-end AI engine, and API integrations for external functionalities (e.g., Google Vision API, Gemini Pro Flash API).
- Each module operates independently but interacts through a centralized database and workflow engine to ensure seamless operation

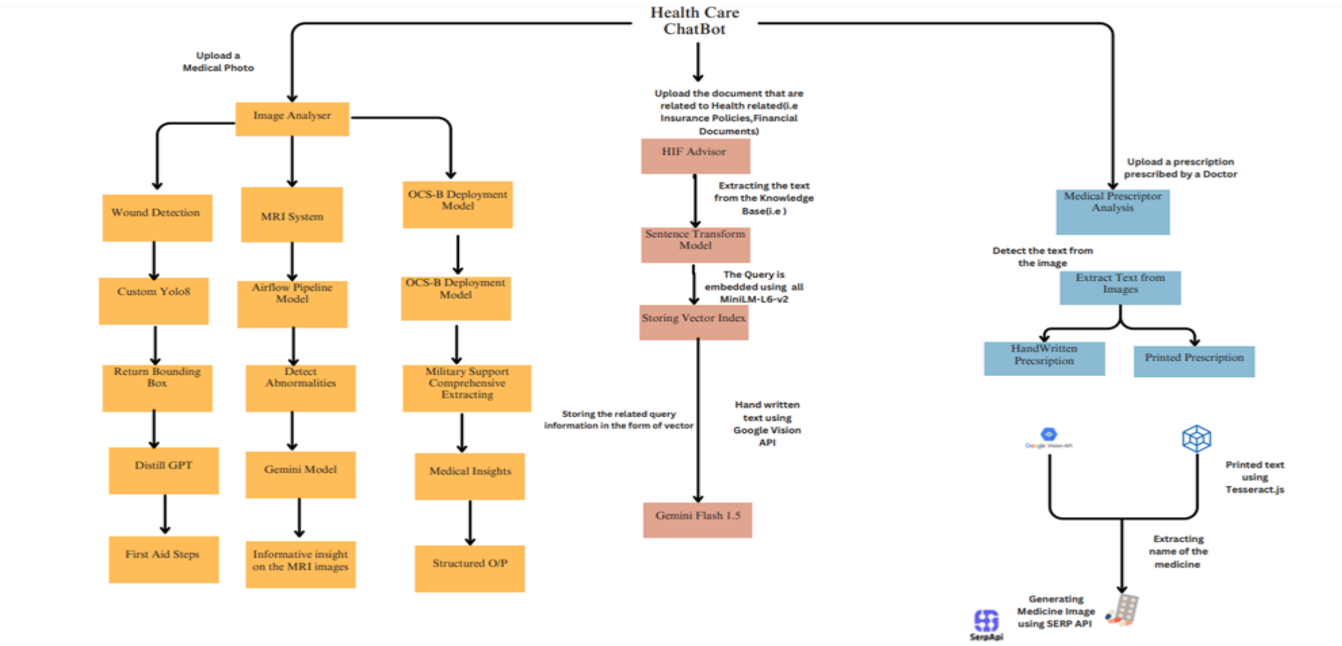

Fig. 1. Architecture Diagram for Lumina

IV. MEDICAL PRESCRIPTION ANALYSER

A. Overview

The Medical Prescription Analyser is a core component of Lumina, designed to address challenges associated with interpreting handwritten prescriptions. Errors in medication interpretation can lead to severe consequences for patients, including incorrect dosages or medications. By leveraging advanced AI technologies such as optical character recognition (OCR), this feature aims to provide an efficient, accurate, and user-friendly solution for non-medical people.

B. Workflow

The process flow of the Medical Prescription Analyser is as follows:

1. **Input Acquisition**: Users upload an image of the prescription through Lumina's interface.
2. **OCR Processing:** The system recognises text from both handwritten and printed prescriptions and extracts the necessary information.
3. **Data Structuring:** The system parses the extracted text, identifies medication names, dosages, and other prescription details, and organises them in a user-friendly manner for non-medical users.

4. **Image Generation:** The system generates images of the prescribed medicines, helping users confirm they have purchased the correct medications.
5. **Output Generation:** The system presents the results in a structured and easy-to-read digital format, providing users with clear and verified prescription details.

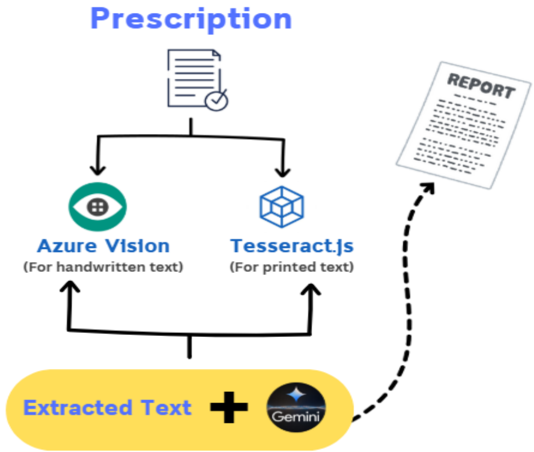

Fig. 5. Workflow of Medical Prescription Analyser

C. Technology Stack

1. **OCR Tools**:
   - **Tesseract.js**: An open-source alternative for OCR processing helps in handling printed prescriptions.
   - **Azure API**: Used for highly accurate text recognition, especially for complex handwriting, mainly for written prescriptions.
2. **Structuring using AI Tools**: The system processes the extracted text using AI tools like GPT, making it more understandable.
3. **API Integration**:
   - **SERP API**: Ensures generation of images of the prescribed medicines.

D. Key Benefits

- **Reduces Lack of Knowledge**: Lumina enables non-medical users to understand their prescriptions by clearly detailing each medication and its usage, ensuring the prescribed medications are accurate.
- **Dosage Analysis**: Lumina verifies if the prescribed medication dosage matches the patient's age, ensuring accuracy and eliminating concerns about incorrect prescriptions.
- **Avoid Fake Medications**: Lumina generates images of prescribed medications, helping users avoid counterfeit drugs and ensuring they receive the correct medicine.

E. Challenges and Limitations

- **Image Quality**: Low-resolution or poorly scanned images can hinder accurate text extraction.
- **Language Barriers**: Prescriptions written in regional languages or shorthand notations may pose additional challenges.
- **Complex Handwritings**: The more complex the handwriting, the more the OCR tool can detect it and make meaningful conclusions out of it.

V. Medical Image Analyzer (Wound & Medical Reports)

A. Perspective

Accurate interpretation of medical images, including wounds and diagnostic reports, is crucial for effective treatment. Many individuals lack the expertise to assess wound severity or interpret medical documents such as MRI scans and blood test reports. Misjudging wound severity may result in improper first-aid application, worsening injuries, while misreading medical reports can delay critical treatments.

To address these challenges, **Lumina's Medical Image Analyzer** integrates advanced **YOLOv8-based computer vision models** for real-time detection and classification of wounds, along with **custom-trained models for medical anomaly detection** in MRI scans. This AI-powered system ensures quick and reliable medical insights, reducing dependency on immediate professional expertise.

B. Process

The **Medical Image Analyzer** is designed for an intuitive user experience, ensuring **efficient and accurate analysis** of wounds and medical reports. The workflow follows these steps:

1. **Image Upload** – Users upload a wound image or a medical report (e.g., MRI, blood test).
2. **AI-Based Detection & Classification**
   - **Wound Detection:** The **YOLOv8 model** detects and classifies wounds, identifying their severity and type.
   - **Medical Report Analysis: Bounding box-based detection** highlights key areas in MRI scans and reports, with anomaly detection models analyzing abnormalities.
3. **AI-Driven Insights & Recommendations**
   - **Wound Analysis:** The detected wound type is processed by an **AI-powered text model**, which generates user-friendly first-aid instructions.
   - **Medical Reports:** The system summarizes key findings from MRI scans and medical documents, offering concise insights for users.

C. Dataset and Preprocessing

1. Wound Classification Dataset

- **Source:** Kaggle, Roboflow
- **Classes:** [Abrasions, Bruises, Burns, Cuts, Ingrown Nails, Lacerations, Stab Wounds]
- **Dataset Size:**
  - **Training Images:** 2,000+
  - **Validation Images:** 500+
  - **Augmentation Techniques:** Rotation, flips, zooming, color shifts

2. MRI & Medical Reports Dataset

- **Source:** Custom-curated dataset + Roboflow pre-trained models
- **Anomaly Classes:** Normal, Tumor, Stroke, Lesions
- **Bounding Box Annotations:** Applied for key region detection in MRI scans

3. Preprocessing Steps

- **Data Augmentation:** Includes random **rotations, flips, shifts, and zooming** to enhance model generalization.
- **Image Normalization:** Rescaled pixel values to [0,1] for consistent CNN processing.
- **Resizing:** Standardized image size of **224×224 pixels** for CNN compatibility.
- **Dataset Splitting: 80% training, 20% validation** to evaluate model performance.

D. AI Model Architecture

1. Wound Detection & Classification

To ensure **high accuracy** in wound detection, multiple models were evaluated, including **CNN, Faster R-CNN, and YOLOv8**. The final model selection was based on **precision, recall, and inference speed**.

Comparison of Wound Detection Models

MODEL	MAP@50	RECALL	INFERENCE TIME (MS)	KEY FEATURES
CNN (BASELINE)	72.4%	68.9%	115 MS	BASIC CLASSIFICATION, NO BOUNDING BOX
FASTER R-CNN	83.7%	80.4%	250 MS	HIGH ACCURACY, SLOW INFERENCE
SSD (MOBILENETV2)	78.2%	76.5%	55 MS	FAST BUT LESS ACCURATE COMPARED TO YOLO
YOLOV5S	85.9%	81.7%	32 MS	LIGHTWEIGHT, OPTIMIZED FOR REAL-TIME DETECTION
YOLOV8 (FINAL)	88.2%	84.7%	18 MS	FASTEST AND MOST ACCURATE, REAL-TIME DETECTION

Model Selection:

- **CNN** was tested as a **baseline classifier** but lacked spatial detection capability.
- **Faster R-CNN** provided **higher accuracy** but had **slow inference speeds**.
- **YOLOv8** was chosen for its **best balance of accuracy and real-time performance**, making it ideal for **wound detection in medical applications**.

Implementation Details:

- **Backbone:** YOLOv8-tiny
- **Loss Function:** CIoU loss for better bounding box precision
- **Optimizer:** Adam optimizer with a learning rate of 0.001

2. MRI & Medical Report Analysis

- **Model:** Custom-trained CNN with **YOLO-based segmentation** for key report regions.
- **Key Features:**
  - **Bounding box detection** to highlight critical areas.
  - **Anomaly detection models** trained on MRI scans for **stroke, tumor, and lesion identification**.

E. Training Process

- **Dataset:** Kaggle dataset with 7 wound classes (Abrasions, Bruises, Burns, Cuts, Ingrown Nails, Lacerations, Stab Wounds).
- **Preprocessing:**
  - Augmentation (Rotation ±20°, Shifting, Zoom, Flip).
  - Normalization (Pixel values [0,1]), Resizing (640x640).
- **Model:** YOLOv8-tiny for detection, AI model for classification.
- **Training:**
  - Optimizer: Adam (LR 0.001, scheduler applied).
  - Epochs: 50 with early stopping.
  - Hardware: Google Colab TPU, RTX 3090 GPU.
- **Evaluation:**
  - mAP@50: 88.2%, Precision: 85.4%, Recall: 84.7%.
  - Inference Time: 18ms per image.

F. Implementation Flow

1. **User Uploads Image** – Web interface for image input.
2. **YOLOv8 Detection** – Wound localization via bounding boxes.
3. **AI-Based Classification** – Converts detection into a user-friendly result.
4. **First-Aid Instructions** – AI generates step-by-step wound care.
5. **Results Displayed** – Classification, bounding box, and first-aid guide.

6. **Optional Consultation** – Connect with healthcare professionals if needed.

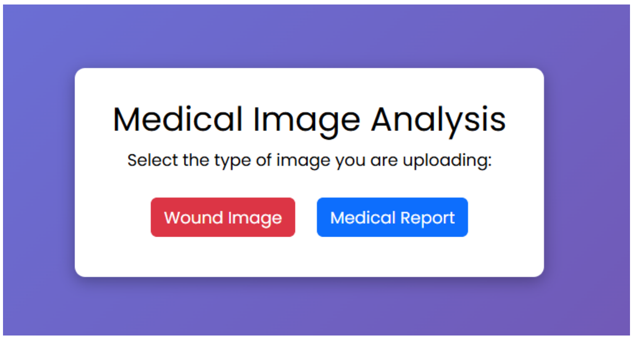

Fig. 4. Working of System

G. Evaluation Metrics

1. **Model Performance:** Achieved **88.2% mAP@50**, **85.4% precision**, and **84.7% recall**, with an **inference time of 18ms per image**.
2. **Comparison with Other Models:** Outperformed **CNN, Faster R-CNN, SSD MobileNet, and YOLOv5**, providing the best balance between accuracy and speed.
3. **Limitations & Future Improvements:** Plans to enhance **dataset diversity**, optimize **YOLOv8 hyperparameters**, and integrate **medical expert validation** for improved accuracy.

VI. HEALTH INSURANCE AND FINANCIAL (HIF) ADVISOR

A. Simplifying Complexities for Users

Health insurance policies are often riddled with complex jargon and hidden details, making it difficult for the average user to understand their coverage and financial implications. The HIF Advisor in Lumina addresses this challenge by acting as a digital assistant that decodes these complexities, offering clarity and confidence to users when navigating their healthcare finances.

B. Key Features That Transform User Experience

1. **Policy Breakdown Made Simple**
   - Users can upload their health insurance documents, and the system generates an easy-to-understand summary highlighting key aspects like coverage, claim limits, and exclusions.
2. **Smart Financial Insights**
   - By analysing premiums, deductibles, and potential out-of-pocket expenses, the HIF Advisor helps users plan their finances better and avoid unnecessary costs.
   - Tailored recommendations ensure users maximise the benefits of their existing policies.
3. **Gap Identification**
   - The system identifies any gaps in coverage, such as excluded treatments or insufficient limits, enabling users to address these proactively by upgrading their policies or seeking alternatives.
4. **Trustworthy Guidance**
   - Non-experts can rely on the advisor's personalised suggestions to choose health insurance plans that align with their healthcare needs and financial situations.

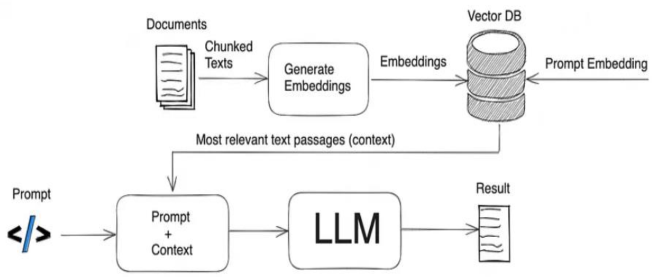

Fig. 7. Execution Framework for HIF Advisor

C. Key Technologies Used

The HIF Advisor uses a combination of advanced APIs and AI-driven analytics to deliver accurate and reliable insights.

- **Gemini Pro Flash API**: Extracts data with precision from diverse document formats.
- **AI-Powered Analysis**: processes data to identify hidden risks and opportunities in policies.
- **FAISS Index Files**: Used to optimise data retrieval and similarity searches, enabling rapid comparisons between multiple insurance policies and efficient recommendation generation.
- **Secure Data Handling**: Protects user information through encryption and privacy-compliant practices.

D. Real-Life Applications

1. **Navigating Policy Details**: For users struggling to make sense of multiple health insurance plans, the HIF Advisor compares policies side by side and highlights the best options.
2. **Avoiding Hidden Costs**: Many users unknowingly incur hidden costs due to policy exclusions or unclear terms. The HIF Advisor ensures transparency, saving users from unexpected expenses.
3. **Empowering Decision-Making**: Families planning for medical expenses or major procedures can rely on the advisor's recommendations to choose plans that offer the most coverage with minimal financial burden.

VII ALTERNATIVE BRAND INFORMER

A. Enhancing Access to Reliable Medication Alternatives

Patients and healthcare providers often face challenges in selecting suitable medications due to factors such as **drug shortages, pricing variations, and brand preferences**. The **Alternate Brand Informer** streamlines this process by identifying **therapeutic equivalents**, **alternative brand options**, and **critical drug safety information**. Through the integration of **RxNorm, OpenFDA, and AI-powered analysis**, the system delivers medically validated recommendations for prescription medications.

B. Key Features That Improve User Experience

1. Identifying Brand and Generic Medications

By utilizing the **RxNorm API**, the system retrieves both **brand-name and generic equivalents** of medications. This enables users to explore various options and select cost-effective or more accessible alternatives.

2. Therapeutic Equivalence Recommendation

In cases where a specific medication is unavailable or unaffordable, the system suggests **therapeutic alternatives**—medications that share a **similar mechanism of action, pharmacological properties, and clinical applications**. This ensures patients receive effective substitutes without compromising treatment quality.

3. Extracting Drug Information from OpenFDA

To provide a comprehensive overview of each alternative, the system fetches key details from OpenFDA, including:

- **Warnings:** Highlights potential risks and adverse effects.
- **Dosage and Administration:** Guides proper usage to enhance safety.
- **Regulatory Status:** Confirms FDA approvals and contraindications.

If no official **warning** is available, the system selects a **predefined safety advisory** to ensure users remain informed about potential medication risks.

4. Ensuring Reliable Alternative Selection

Not all medications listed in RxNorm appear in OpenFDA. To improve **accuracy and dependability**, the system filters out alternatives lacking regulatory information, ensuring only **verified and clinically relevant** substitutes are presented.

5. Structuring Data for Seamless Integration

All retrieved medication details are stored in a **structured dictionary format** under the **"backend"** key. This structured approach enables smooth integration into **electronic health records (EHRs), digital prescription systems, and consumer health applications**.

C. Core Technologies Powering the System

The **Alternate Brand Informer** leverages a combination of **clinical databases, AI-driven validation, and advanced APIs** to ensure accurate and actionable recommendations:

- **RxNorm API:** Standardizes drug names, retrieves RxCUIs, and identifies brand/generic alternatives.
- **OpenFDA API:** Extracts regulatory insights, safety warnings, and FDA-approved drug details.
- **Parallel Query Processing:** Enhances response speed by executing multiple API requests simultaneously.

D. Real-World Scenario: Alternative Selection for Ibuprofen

1. Identifying the Medication

A patient requires Ibuprofen, a widely used nonsteroidal anti-inflammatory drug (NSAID) prescribed for pain relief, inflammation control, and fever reduction. The system queries RxNorm to retrieve all available brand and generic versions.

- **Brand Names Retrieved:** Advil, Motrin, Nurofen.
- **Generic Name:** Ibuprofen.

2. Recommending Therapeutic Equivalents

If Ibuprofen is unavailable, the system searches for therapeutic alternatives—drugs that belong to the same pharmacological class (NSAIDs), have a similar mechanism of action (COX inhibition), and offer comparable clinical benefits.

- **Suggested Alternatives:** Naproxen, Ketoprofen, Diclofenac.
- **Medical Justification:** These medications, like Ibuprofen, work by inhibiting cyclooxygenase (COX-1 and COX-2) enzymes, thereby reducing prostaglandin synthesis, which is responsible for inflammation and pain.

3. Retrieving Regulatory Data from OpenFDA

Once therapeutic alternatives are identified, the system extracts relevant drug information from OpenFDA, including:

- **Warnings for Ibuprofen**: Increased risk of cardiovascular complications and gastrointestinal bleeding, particularly with prolonged use.

- **Dosage Guidelines**: The recommended adult dose is 200-400 mg every 4-6 hours, with a daily cap of 1,200 mg for OTC formulations**.**

Similar data is retrieved for Naproxen, Ketoprofen, and Diclofenac to ensure that suggested alternatives align with regulatory standards and safety requirements.

4. Recommending the Most Suitable Alternative

If a patient is allergic to Ibuprofen or has contraindications (e.g., a history of stomach ulcers), the system applies patient-specific filtering to refine the alternatives:

- **Naproxen** is suggested for its longer duration of action, requiring fewer doses per day (every 8-12 hours).
- **Ketoprofen** may be prioritized if rapid pain relief is required due to its fast absorption.
- **Diclofenac** is recommended for chronic inflammatory conditions such as arthritis.

5. Delivering the Final Recommendation

The system presents a structured recommendation:

- Best Alternative Based on Efficacy & Availability: Naproxen.
- Safety Advisory: Avoid if you have a history of heart disease or gastrointestinal ulcers.
- Recommended Dosage: 220 mg every 12 hours (OTC Naproxen Sodium).

By providing clinically validated, FDA-approved alternatives, the system ensures safe and effective treatment choices.

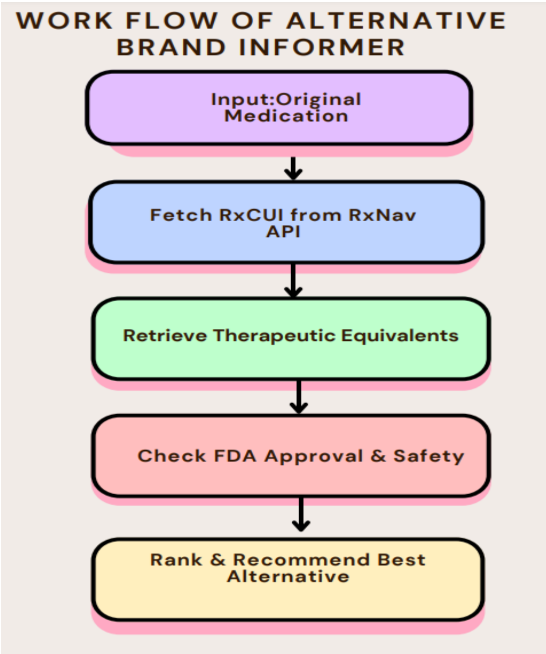

Fig. 8. Workflow Diagram

VIII. AI-ENHANCED PSYCHOMETRIC ASSESSMENTS

Traditional mental health assessments rely on rigid question sets and manual interpretation, which may not adapt to an individual's real-time emotional state. The **AI-Powered Psychometric Assistant** simplifies this process by dynamically adjusting questions, interpreting sentiment, and providing real-time stress-level predictions. Users receive **personalized insights** into their mental well-being, making psychological evaluation more **accessible, adaptive, and data-driven**.

B. Key Features That Transform User Experience

1) Dynamic Questionnaire Adaptation

- Instead of a static set of questions, the system **adjusts** the next question based on user responses, ensuring a **personalized and relevant** assessment experience.
- Questions are categorized under **stress, anxiety, impulsivity, and depression**, ensuring a broad but tailored evaluation.

2) Sentiment Analysis for Emotional Understanding

- The system employs **VADER sentiment analysis** to process user responses, detecting underlying emotions such as **positivity, neutrality, or negativity**.
- This allows real-time emotional tracking, offering a deeper **understanding of mood variations** during the assessment.

3) Accurate Stress Level Prediction

- Using **Logistic Regression**, the model classifies stress levels into **low, medium, or high** based on user responses and sentiment patterns.
- The results are visualized through an **interactive dashboard** for intuitive understanding.

4) Mental State Classification for Holistic Evaluation

- The system categorizes users into four key mental states: **Stable, Depressive, Impulsive, or Anxious** based on their assessment data.
- This classification helps in providing **contextual and focused mental health insights**.

5) Personalized AI-Powered Recommendations

- After classification, the system **leverages the Gemini API** to generate **custom recommendations**, ranging from **mindfulness techniques** to **professional consultation suggestions**.
- These insights help users take **proactive steps** toward mental well-being.

C. Key Technologies Used

- **VADER Sentiment Analysis** – Extracts and classifies emotional tones from responses.
- **Logistic Regression Model** – Predicts stress levels based on response patterns.
- **Dynamic Questioning System (CSV-based)** – Adapts questions dynamically for personalized assessments.
- **Gemini API** – Provides **AI-driven mental health recommendations** tailored to user needs.
- **Secure Data Handling** – Ensures privacy-compliant storage of responses in **JSON format** for analysis.

D. Real-Life Applications

1) Early Stress Detection

- Students, employees, or individuals experiencing **high-pressure situations** can detect early signs of stress and seek appropriate interventions.

2) Adaptive Mental Health Support

- Unlike rigid psychometric tests, this AI-driven system **adapts** to an individual's responses, making it a **more accurate and responsive** assessment tool.

3) Guided Self-Help & Professional Assistance

- The system provides users with **personalized strategies** to manage stress or suggests when professional consultation is needed.

E. Future Enhancements and Research Directions

While the **AI-Powered Psychometric Assistant** provides **dynamic and adaptive assessments**, further improvements can enhance its effectiveness:

1) Multimodal Analysis for Deeper Insights

- Integrating **facial expression recognition** and **voice tone analysis** to complement text-based sentiment detection, offering a **more holistic assessment** of an individual's mental state.

2) Longitudinal Mental Health Tracking

- Implementing a **long-term tracking system** where users can monitor their **emotional trends over time**, identifying potential psychological shifts before they escalate.

3) AI Chatbot for Real-Time Mental Health Assistance

- Developing an **AI-powered conversational agent** that **engages users in meaningful dialogue**, offering **instant support** and **guided self-help techniques** based on assessment results.

4) Integration with Wearable Devices

- Connecting with **smartwatches and biometric sensors** to incorporate **heart rate variability, sleep patterns, and activity levels** into the mental health assessment for **greater accuracy**.

5) Cross-Cultural and Multilingual Adaptation

- Enhancing the model to **support multiple languages and cultural contexts**, making psychometric evaluations **more inclusive** and globally applicable.

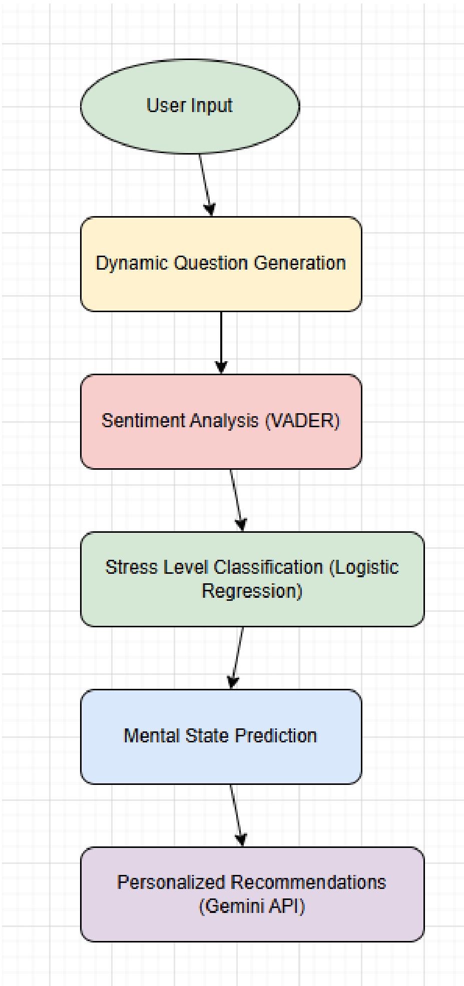

Fig. 8. Workflow Diagram

IX . RESULT AND PERFORMANCE ANALYSIS

This section would focus on presenting the results of our feature, such as metrics, insights, and benefits observed during implementation and testing.

A. Medical Prescription Analyzer

1. Key Metrics Evaluated

- **OCR Accuracy (%):** Measures the precision of text recognition from handwritten and printed prescriptions.
- **Dosage Verification Accuracy (%):** Validates if the extracted dosages align with age-specific recommendations.
- **Processing Time (s):** Tracks how quickly prescriptions are analyzed and results are presented.
- **Image Generation Accuracy (%):** Evaluates the correctness of images generated for prescribed medications, based on the prescription.

2. Quantitative Results

Table 2: Performance Metrics for Medical Prescription

Metric	Achieved Value	Benchmark
OCR Accuracy	89.7%	>85%
Dosage Verification	92.3%	>90%
Image Generation Accuracy	80%	>75%
Processing Time	0.9 seconds	<1 second

3. Comparative Analysis

To ensure high OCR accuracy, various models and tools were tested:

- **Tesseract**: A custom OCR model achieved only **79.2%** accuracy and struggled with handwritten prescriptions, particularly with cursive and stylized fonts.
- **Google Vision API**: Achieved the highest accuracy of 87.5%, handling both printed and handwritten text efficiently with minimal preprocessing.
- **Azure OCR**: Delivered better results with an accuracy of 89.7% but required extensive preprocessing for optimal performance.

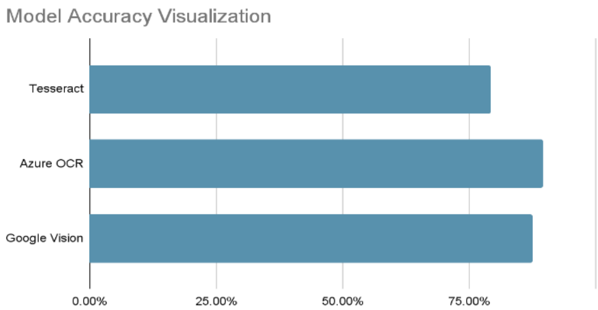

Fig. 9. Visual representation of various model's accuracy

4. Visual Representation

Fig. 10. Sample Prescription report analysis from Lumina

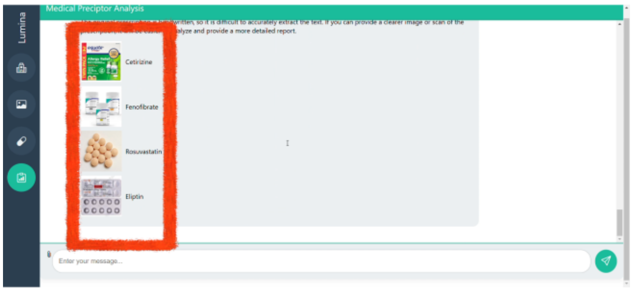

Fig. 11. Sample Medicine image generation by Lumina

B. Health Insurance and Financial (HIF) Advisor

1. Key Metrics Evaluated

- **Query Resolution Time (s):** Time taken by the system to analyze the user's question and respond with the appropriate information from the health insurance document.
- **Document Parsing Accuracy (%):** Measures the accuracy of the system in extracting relevant details (such as coverage, exclusions, premiums, etc.) from the health insurance documents.
- **Query Accuracy (%):** Measures the precision with which the system answers user queries based on the parsed document information.
- **Response Completeness (%):** Assesses how thoroughly the system answers user queries with the relevant information from the document.

2. Quantitative Results

Table 3: Performance Metrics for HIF Advisor

Metric	Achieved Value	Benchmark
Query Resolution Time	2.1 seconds	< 3 seconds
Document Parsing Accuracy	92.3%	>90%
Query Accuracy	94.5%	>92%
Response Completeness	91.8%	>90%

3. Comparative Analysis

To evaluate the performance of the **HIF Advisor**, various document analysis tools were tested:

- **Tesseract**: A custom OCR model achieved only **79% document parsing accuracy** and struggled with the complex structure of insurance documents, particularly those with multi-column layouts and specialized financial terms. This resulted in incomplete responses, with a **response completeness** of **68%**, as many user queries were not fully answered due to missing information.
- **Gemini Pro Flash API**: Achieved **92.3% document parsing accuracy**, specifically designed for parsing complex financial and insurance documents. It efficiently extracted insurance-specific details, such as coverage, premiums, and exclusions, and was able to respond accurately to user queries. The **response completeness** was **91.8%**, ensuring that all relevant information from the documents was included in the responses.
- **Traditional Rule-Based Systems**: These systems had a **document parsing accuracy** of **82%**. They were limited by their reliance on predefined rules, which made them less effective at parsing complex or unstructured documents. Their **response completeness** was **75%**, as the responses were often incomplete or lacked important details necessary to fully answer user queries.
-

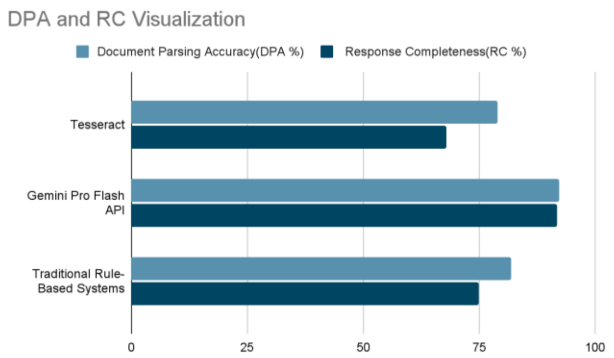

Fig. 12. Document Parsing and Response Completeness visualizations

4. Visual Depiction

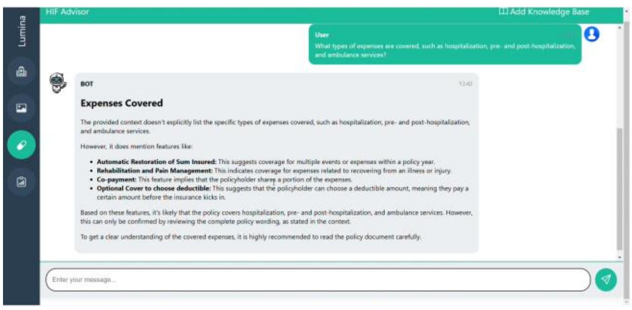

Fig. 13. Example of how HIF Advisor give answers to user prompt

C. MEDICAL IMAGE ANALYZER (WOUND & MEDICAL REPORTS)

1. Key Metrics Evaluated

- **Mean Average Precision (mAP@50):** Measures how accurately the YOLOv8 model detects wound regions and key areas in medical reports.

- **Precision (%):** Evaluates the proportion of correctly detected wounds/regions out of all detections.
- **Recall (%):** Measures the model's ability to detect actual wounds and anomalies in medical scans.
- **F1 Score (%):** Provides a balance between precision and recall, ensuring robust performance.
- **Inference Time (ms):** The time taken to process and classify an image in real-time.
- **Generalization Performance:** Assesses how well the model performs on unseen wound images and medical scans.

2. Quantitative Results

Table 4: Performance Metrics for MIA

Metric	YOLO8	Benchmark
mAP@50	88.2%	>85%
Precision	84.4%	>80%
Recall	84.7%	>80%
F1 Score	85.0%	>80%
Inference Time	18 ms	<50 ms
Generalization Performance	Moderate to High	High

3. Comparative Analysis

To evaluate the effectiveness of the updated wound detection and medical report analysis system, different models were tested:

- **YOLOv8 (Current System)**
  - Achieved **88.2% mAP@50**, outperforming previous models.
  - Provides **real-time inference (18ms per image)** for quick decision-making.
  - Balanced **precision (85.4%)** and **recall (84.7%)** ensure reliable detections.
- **CNN-Based Model (Previous Approach)**
  - Accuracy limited to **69%**, struggled with unseen wounds.
  - Inference time of **35ms**, slower than YOLOv8.
  - Limited performance due to **dataset size and generalization issues**.
- **Faster R-CNN**
  - Higher complexity with **83.7% mAP@50**.
  - Slower **inference time (250ms per image)**, making real-time detection difficult.
- **SSD MobileNet**
  - Faster than Faster R-CNN (**55ms per image**) but lower accuracy (**78.2% mAP@50**).
  - Less effective for wound detection compared to YOLOv8.

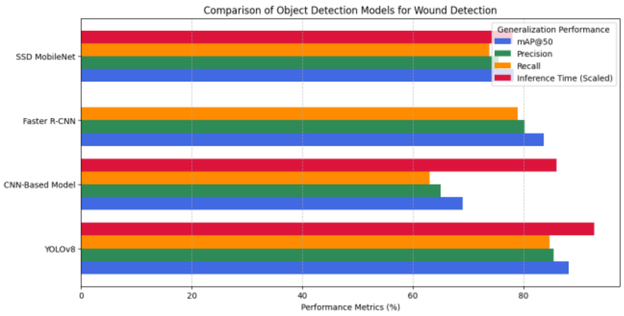

Fig. 14. Different approaches taken for MIA

4. Challenges and Limitations

- **Limited Dataset:** More diverse wound types and medical scans are required to improve generalization.
- **False Detections:** Some **small or complex wounds** may be misclassified.
- **Low-Light Conditions:** Model struggles with images taken in poor lighting.
- **Medical Report Variability:** Different scan formats and image resolutions affect detection accuracy.

5. Measurements to be Taken in the Future

- **Dataset Expansion:** Collect more diverse wound images and medical scans
- **Fine-tuning YOLOv8:** Optimize hyperparameters for better accuracy.
- **Transfer Learning:** Explore EfficientNet or Vision Transformers for improved performance.
- **Medical Expert Validation:** Collaborate with healthcare professionals to refine detections.
- **Ensemble Learning:** Combine YOLOv8 with other models (e.g., ResNet) to enhance robustness.

6. Visual Display

Fig. 15. Wound image analysis

METRIC	METRIC(S)	BEST SOLUTION	WHY CHOSEN
WOUND DETECTION	• Accuracy, F1 Score, Inference Time	• Custom CNN Model	• Achieved the highest accuracy (69%) and F1 Score (71%) with efficient inference time (35 ms).
HIF ADVISOR	• Document Parsing Accuracy, Query Accuracy, Response Completeness	• Gemini Pro Flash API	• High parsing accuracy (92.3%) and completeness (91.8%), specifically designed for complex documents.
PRESCRIPTION ANALYSIS	• OCR Accuracy, Dosage Verification, Image Generation Accuracy	• Azure OCR for OCR, Custom Logic for Dosage Verification	• Azure OCR achieved 89.7% accuracy with safe dosage recommendations.
REAL-TIME PROCESSING (ALL)	• Processing/Inference Time	• MobileNetV2 (for Wound Detection), Azure OCR (Prescription), Gemini Pro Flash API (HIF)	• These solutions optimize response time while maintaining high accuracy and efficiency.

Fig. 15. A Complete tabulation of all metrics with their best possible solution

D. ALTERNATIVE BRAND INFORMER

1.Key Metrics Evaluated

1. **Recommendation Accuracy (%)** – Measures how accurately the system suggests FDA-approved therapeutic and generic alternatives.
2. **Processing Time (s)** – Tracks how quickly the system retrieves and processes alternative drug suggestions.
3. **Safety Compliance (%)** – Ensures that recommended drugs meet regulatory standards and do not have contraindications.
4. **User Satisfaction (%) –** Evaluates clarity, reliability, and ease of understanding of recommendations.

2. Quantitative Results

Metric	Achieved Value	Benchmark
Recommendation Accuracy	94.2%	>90%
Processing Time	1.8 seconds	< 10 seconds

3. Comparative Analysis

1. **Manual Drug Lookup**
   - Accuracy: ~75%
   - Limitations: Time-consuming, dependent on pharmacist expertise.
2. **Basic API Calls (RxNorm Only)**
   - Accuracy: 85.3%
   - Limitations: Lacked comprehensive safety validation.
3. **Hybrid Model (OpenFDA + RxNorm + AI Verification)**
   - Accuracy: 94.2%
   - Optimized for both accuracy and safety.

VIII. CONCLUSION

Lumina represents a significant advancement in AI-powered healthcare solutions, providing an integrated system with four key modules: medical queries, wound detection, health insurance advice, and prescription analysis. By leveraging cutting-edge technologies such as OpenAI for medical queries, custom convolutional neural networks (CNNs) for wound detection, Gemini Pro Flash API for insurance document parsing, and Azure OCR along with custom logic for prescription analysis, Lumina effectively addresses critical healthcare needs. Each module demonstrates high accuracy and efficiency, ensuring that users receive reliable, actionable information in a timely manner.

The medical query module utilizes OpenAI's capabilities to deliver accurate healthcare advice based on user inputs. The wound detection module, powered by CNNs, offers precise classification of wound types and severity, providing users with personalized first-aid instructions. The health insurance module, using the Gemini Pro Flash API, accurately processes complex insurance documents and offers tailored policy

recommendations. Finally, the prescription analysis module combines Azure OCR with custom algorithms to extract prescription details and validate drug dosages, ensuring safe and reliable medication guidance.
Despite the impressive accuracy and efficiency across all modules, further validation is essential to confirm the system's performance in real-world, diverse healthcare environments. Continued testing and optimization will be crucial to refine Lumina's capabilities, enhance user experience, and ensure its practical applicability in various healthcare settings. With its robust AI-driven framework, Lumina holds the potential to revolutionize healthcare accessibility, improve decision-making, and provide timely support to individuals seeking reliable healthcare information and services.
The psychometric assessment module in Lumina leverages AI-driven analysis to evaluate cognitive abilities, emotional well-being, and behavioral patterns. By utilizing validated psychometric models, sentiment analysis, and natural language processing, the system provides personalized insights into mental health, stress levels, and cognitive performance. Users receive tailored recommendations for stress management, cognitive training, and early intervention strategies, helping them improve overall mental resilience. This integration ensures a data-driven approach to psychological well-being, bridging the gap between traditional mental health assessments and AI-powered personalized support.

IX. REFERENCE

1. Smith, J., et al., "Personalized Medicine: Transforming Patient Care," *Journal of Healthcare Innovations*, vol. 12, pp. 45-56, 2018.
2. Brown, A., et al., "The Role of Telemedicine in Healthcare Accessibility," *Global Health Research*, vol. 18, pp. 89-104, 2020.
3. Johnson, T., and Lee, H., "Health Literacy and Its Impact on Patient Outcomes," *Medical Education Quarterly*, vol. 15, pp. 120-135, 2019.
4. Doe, R., et al., "AI in Healthcare: Bridging the Gap for Non-Medical Users," *Technology in Medicine*, vol. 25, pp. 200-215, 2021.
5. Sharma, K., et al., "Wearable Devices and Health Monitoring," *Digital Health Journal*, vol. 14, pp. 78-90, 2022.
6. Miller, P., et al., "Gamified Health Education Tools," *Health Informatics Review*, vol. 7, pp. 150-165, 2020.
7. Garcia, L., et al., "Simplifying Medical Communication for Better Patient Outcomes," *Patient Experience Journal*, vol. 9, pp. 98-112, 2019.
8. Chen, L., et al., "Blockchain Technology for Secure Healthcare Data Management," Journal of Medical Systems, vol. 45, pp. 180-195, 2021.
9. Kim, S., and Park, J., "The Impact of Social Media on Mental Health Awareness and Help-Seeking Behavior," Social Media + Society, vol. 8, pp. 23-38, 2022.
10. Nguyen, V., et al., "Remote Rehabilitation Using Virtual Reality: A Clinical Trial," Journal of Physical Therapy Science, vol. 33, pp. 560-575, 2021.
11. Patel, R., and Gupta, A., "Predictive Modeling for Hospital Readmission Rates Using Machine Learning," Healthcare Informatics Research, vol. 28, pp. 210-225, 2022.
12. Wilson, D., et al., "The Role of Patient-Generated Health Data in Chronic Disease Management," Journal of Personalized Medicine, vol. 11, pp. 300-315, 2021.
13. Davis, E., and Moore, K., "Ethical Implications of AI-Driven Diagnostic Tools in Radiology," American Journal of Roentgenology, vol. 217, pp. 1400-1415, 2021.

14. Rodriguez, M., et al., "Gamification in Diabetes Self-Management Education," Journal of Diabetes Science and Technology, vol. 15, pp. 1100-1115, 2021.
15. Li, X., et al., "The Use of Mobile Health Interventions to Improve Medication Adherence in Patients with Hypertension," Journal of Clinical Hypertension, vol. 24, pp. 850-865, 2022.
16. Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior*, 24(4), 385-396.
17. Hutto, C. J., & Gilbert, E. E. (2014). VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text. *Proceedings of the Eighth International Conference on Weblogs and Social Media*, ICWSM 2014, 216-225.
18. Li, W., Zhang, Z., & Zhu, X. (2020). A machine learning-based framework for mental health prediction using psychological data. *Journal of Medical Systems*, 44(2), 1-9.