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HospAI - An AI Powered Hospital Management System

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Abstract: HospAI is an AI-powered hospital management system designed to integrate intelligent diagnostic support with digital healthcare services. The system combines deep learning techniques such as Convolutional Neural Networks (CNNs) for bone fracture detection from X-ray images and machine learning models for cardiovascular disease prediction using ECG data. In addition to diagnostic capabilities, the platform provides a unified solution for hospital management, including appointment scheduling, patient record handling, and administrative monitoring through web and mobile interfaces. By bridging the gap between clinical diagnostics and hospital operations, the proposed system enhances efficiency, accuracy, and accessibility in healthcare delivery.

Index Terms: Artificial Intelligence (AI), Deep Learning, Clinical Decision Support System, Explainable AI (XAI), Predictive Analytics, Medical Imaging, Risk Prediction

I. INTRODUCTION

In today's rapidly evolving healthcare environment, the integration of artificial intelligence (AI) has become increasingly important for improving diagnostic accuracy, operational efficiency, and patient care. Conventional hospital management systems largely depend on manual data handling and human interpretation of medical reports, which are often timeconsuming, inconsistent, and prone to error. With rising patient volumes and growing data complexity, these limitations have become more pronounced.

Recent advances in AI and machine learning have enabled the automation of both diagnostic and administrative tasks. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated strong performance in medical image analysis, including fracture detection from Xrays and MRI scans [3] [4] [5] [6]. In parallel, optical character recognition (OCR) and machine learning techniques allow rapid and accurate extraction of information from laboratory reports.

By integrating these technologies, an intelligent healthcare management framework can be developed to support clinical decision-making while improving administrative transparency. Such a system assists doctors with AI-based diagnostics, provides departmental performance insights to Heads of Departments, and supports data-driven decision-making, ultimately contributing to a more efficient and patient-centric healthcare ecosystem.

1) Major Highlights of our work are as follows: AI-based bone fracture detection using X-ray images with Grad-CAM visualization for interpretability.
2) Cardiovascular risk prediction using machine learning models based on ECG and clinical parameters.
3) Patient-centric mobile application enabling appointment booking, medical data upload, and report access.
4) Storage of annotated diagnostic outputs for future reference and analysis.
5) Provides an Admin module for monitoring system activities, managing resources, and generating overall reports for efficient hospital administration..

II. LITERATURE SURVEY

A. Dashboards and Clinical Decision Support

Tsai et al. [1] proposed an AI-powered hospital dashboard for real-time prediction of adverse outcomes in emergency patients. Implemented at Chi Mei Medical Center, it used a four-tier SOA architecture integrated with hospital systems and trained ML/DL models (MLP, Random Forest, XGBoost) on ten years of EMR data. The best AUC model was deployed for continuous monitoring, risk alerts, and visual decision support, improving clinical decision-making and efficiency.

Khairat et al. [2] reviewed the impact of clinical dashboards on care quality, workflow, and clinician satisfaction. Analyzing ICU and emergency settings, the study found that real-time EHR visualizations reduce cognitive load, improve situational awareness, and enhance usability. Effectiveness depends on design, information prioritization, and workflow integration, highlighting dashboards as key tools for clinical decision support.

B. Fracture Detection and Orthopedic Imaging

Rashedur Rahman et al. [3] proposed a two-step transfer learning approach for pelvic fracture detection using synthetic X-rays from 3D-CT scans. A ResNet-101 DCNN was pretrained on DRRs and fine-tuned on real X-rays, reducing domain gap issues. DRR20 achieved the best AUROC (0.9327 visible, 0.8014 invisible fractures). Grad-CAM improved interpretability. Evaluated on 315 patients, the study showed synthetic data enhances performance, though broader validation is needed.

Zhihao Su et al. [4] reviewed over forty deep learning studies on fracture detection using models like Faster R-CNN, U-Net, DenseNet, EfficientNet, and GANs across datasets such as MURA. Metrics included accuracy, recall, AUC, and mAP. Deep learning outperformed traditional methods but faced issues like data imbalance, limited interpretability, and poor generalization, highlighting transfer learning and XAI as future directions.

Haider A. Alwzwazy et al. [5] proposed FracNet, integrating self-supervised pretraining, feature fusion (Xception, MobileNetV2, EfficientNet), and attention mechanisms. Trained on 50,000+ X-rays and tested on 10,763 images, it achieved 100% accuracy with strong generalization. Grad-CAM enabled explainability, outperforming models like ResNet and U-Net, though with higher computational cost.

Enrique Queipo-de-Llano et al. [6] proposed a twinsurrogate XAI framework combining YOLOv5, ResNet-18, Grad-CAM, CBR, and LLMs for fracture diagnosis with visual and textual explanations. Evaluated on 1,018 X-rays, it achieved high accuracy and usability (4.3/5), though limited by dataset diversity and lack of real-time validation.

C. Cardiovascular Risk Prediction

Ahmed M. Alaa et al. [7] proposed AutoPrognosis, an AutoML framework for CVD risk prediction using 423,604 UK Biobank records. It optimized and ensembled models like XGBoost, Random Forest, and Neural Networks across 473 variables using Bayesian optimization. It achieved AUC 0.774, outperforming Framingham (0.724) and Cox PH (0.758), identifying 368 additional cases and novel predictors such as walking pace. Despite limitations in biomarkers and diversity, it showed AutoML improves prediction.

Fatma M. Talaat et al. [8] proposed CardioRiskNet, a hybrid explainable AI framework integrating attention mechanisms, active learning, and SHAP-based interpretability. Evaluated on heart disease datasets, it achieved 98.7% accuracy and outperformed CNN, SVM, and MLP models. Key predictors included serum creatinine and ejection fraction. The model improves accuracy, adaptability, and transparency.

Sorif Hossain et al. [9] reviewed 79 studies (486 models) on AI-based CVD prediction. While models showed improved performance, major issues included poor reproducibility, lack of external validation, and bias. Only 2% met validation standards. The study introduced an Independent Validation Score (IVS) and emphasized frameworks like TRIPOD-AI for clinical reliability.

Stephen F. Weng et al. [10] evaluated ML models on 378,256 patients using routine clinical data. Neural networks achieved the best AUC (0.764), outperforming ACC/AHA (0.728) and identifying 355 additional cases. The study showed ML captures complex relationships but highlighted interpretability challenges, stressing the need for explainable AI.

III. METHODOLOGY

The HospAI system is designed as an integrated AI-driven hospital management platform combining diagnostic intelligence with web and mobile healthcare services. The methodology follows a modular approach consisting of data acquisition, preprocessing, model development, system integration, and deployment.

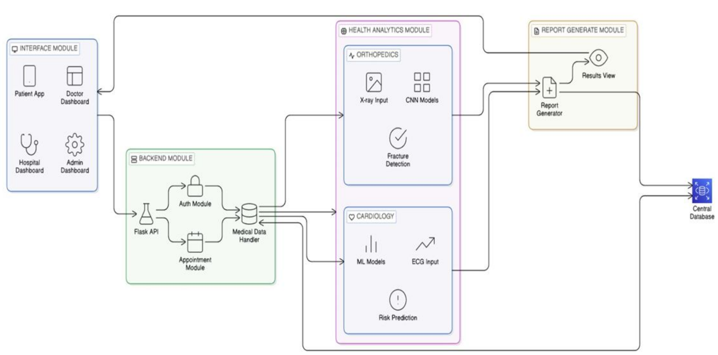

Fig. 1: System architecture

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A. Interface Module

- Acts as the front-end layer of the HospAI system.
- Includes Patient App, Doctor Dashboard, Hospital Dashboard, and Admin Dashboard.
- Allows users to book appointments, upload medical data, and view reports.
- Enables doctors and administrators to monitor and manage system activities.
- Displays AI-generated diagnostic results in a userfriendly format.
- Communicates with the backend by sending requests and receiving results.

B. Backend Module

- Handles the core functionality of the HospAI system.
- Manages communication between the interface and AI modules.
- Processes API requests using the Flask framework.
- Controls services such as authentication, appointment management, and medical data handling.
- Forwards medical data such as X-rays and ECG signals to the health analytics module for analysis.

C. Health Analytics Module

It is split into two parts:

1) Orthopedics Module:

- Performs bone fracture detection from X-ray images using a hybrid AI approach.
- Preprocesses input images by converting to grayscale, resizing, and enhancing contrast.
- Utilizes a multi-model deep learning ensemble consisting of TorchXRayVision DenseNet, ResNet50, and DenseNet121.
- Applies test-time augmentation to improve prediction stability and robustness.
- Combines model outputs using a weighted ensemble strategy to generate accurate predictions.
- Integrates Grad-CAM to produce heatmaps for localizing fracture regions and improving interpretability.
- Employs computer vision techniques such as bone segmentation, cortex continuity analysis, and Hough transform for fracture line detection.
- Uses trabecular texture and intensity asymmetry analysis to detect internal structural abnormalities.
- Combines deep learning, Grad-CAM, and computer vision outputs to compute a final confidence score.
- Highlights detected fracture regions using bounding boxes for visual interpretation.

2) Cardiology Module:

- Performs heart disease risk prediction using clinical and ECG-based parameters.
- Utilizes an ensemble of machine learning models including Random Forest, Gradient Boosting, Support Vector Machine, and Multilayer Perceptron.
- Preprocesses input data using feature scaling and normalization to improve model performance.
- Applies data augmentation techniques to enhance generalization and handle limited dataset size.
- Combines predictions from multiple models using a weighted ensemble approach to generate a final risk score.
- Provides probabilistic output indicating the likelihood of cardiovascular disease.
- Includes an explainability module that identifies key risk factors such as age, cholesterol, blood pressure, and ECG parameters.
- Analyzes ECG signals and images to extract features such as heart rate, rhythm irregularity, and ST-segment changes.
 Generates detailed diagnostic results along with risk factor analysis to support clinical decision-making.

D. Output Module

- Converts AI predictions into understandable diagnostic results.
- Generates structured medical reports using a report generator.
- Includes outputs such as fracture detection results, heart risk analysis, and visualizations.
- Organizes results in a clear and readable format.
- Displays final reports to users through system dashboards.

IV. RESULTS AND DISCUSSIONS

The HospAI system was successfully developed and implemented as an integrated platform consisting of a web-based interface and an Android application.

A. *Patient Application*

The patient application allows users to book appointments, upload medical data, and view diagnostic reports. It also provides features such as medicine reminders and doctor recommendations.

- As shown in Fig 2 secure login and registration are provided to patients, enabling access to features such as appointment booking, medical data upload, and report viewing.

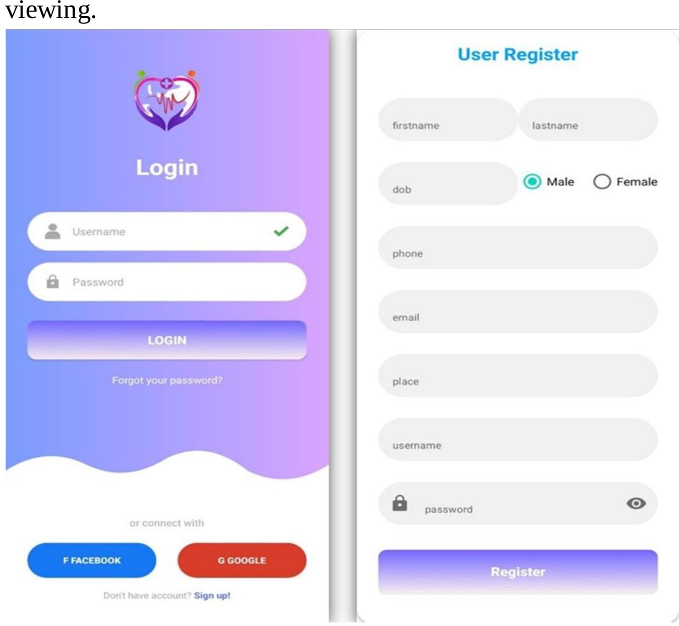

Fig. 2: Login and Registration

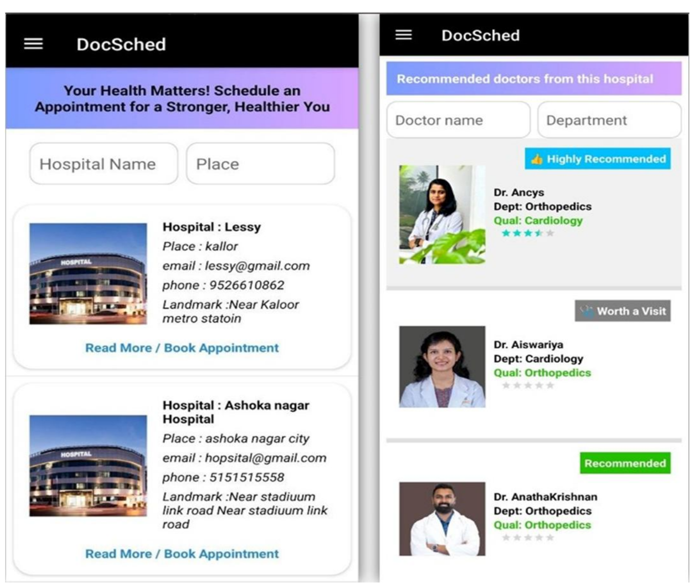

Fig. 3: Appointment Booking

- From Fig 3 Appointment Booking feature allows patients to select from a list of available hospitals within the system.
- Patients can view doctors associated with the selected hospital along with their specialization and availability.
- A recommendation system suggests suitable doctors based on user reviews, ratings, and preferences.
- Patients can choose convenient time slots from the available schedule of the selected doctor.

B. Web Platform Interface

The web platform provides a centralized interface for doctors, hospital staff, and administrators to manage system operations. The website ensures smooth interaction with backend services for real-time data processing and updates.

- The Login Page in Fig 4 enables doctors, hospitals, and administrators to securely access the system using authenticated credetials, ensuring role-based access to respective dashboards.
- The Hospital Registration page shown in Fig 5 allows new hospitals to register enabling their inclusion in the system. The admin decides whether to approve or reject the hospital's request for registration

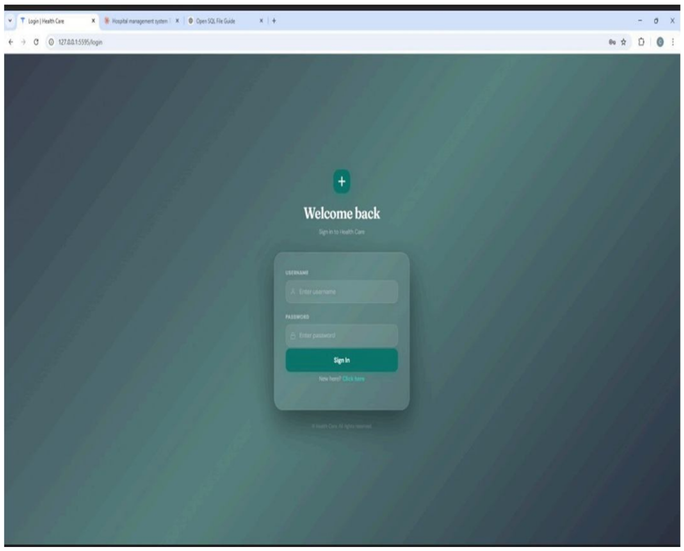

Fig. 4: Login Page

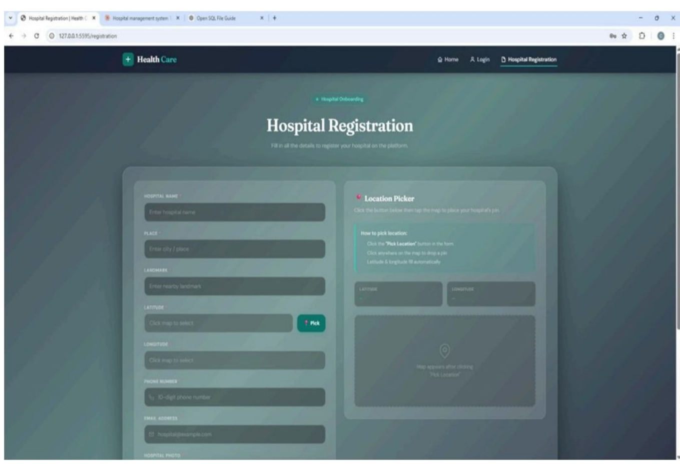

Fig. 5: Hospital Registration

1) Heart Disease Prediction

The Heart Disease Prediction shown in Fig 6 utilizes machine learning models to analyze ECG data and predict the risk of cardiovascular diseases, supporting early diagnosis and clinical decision-making.

- The system is implemented using an ensemble of machine learning models, including Random Forest, Gradient Boosting, Support Vector Machine, and Multilayer Perceptron, to improve prediction accuracy and robustness.
- The models are trained on the UCI Heart Disease dataset, consisting of multiple clinical parameters such as age, cholesterol level, blood pressure, chest pain type, and ECG-related features.

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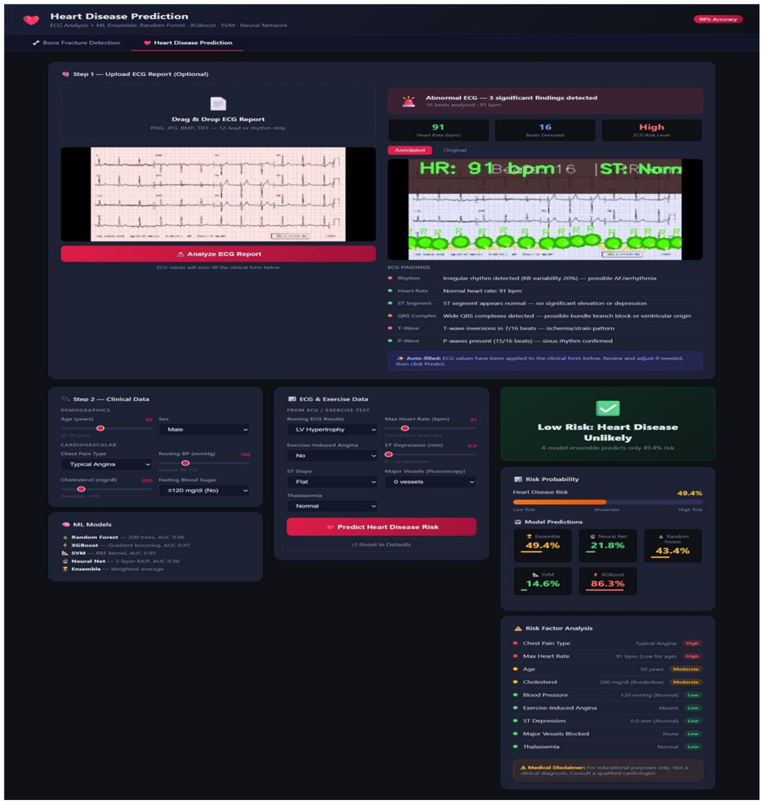

Fig. 6: Heart Disease Prediction

- Data preprocessing includes feature scaling using standardization techniques and data augmentation through noise-based sample generation to enhance model generalization.
- A weighted ensemble strategy is employed to combine predictions from individual models, where each model contributes based on its performance, resulting in a final probabilistic risk score.
- The system outputs both binary prediction and probability score, indicating the likelihood of cardiovascular disease.
- An explainability module evaluates key risk factors such as age, cholesterol, blood pressure, chest pain type, heart rate, and ST depression, categorizing them into high, moderate, and low impact levels.
- The system also incorporates ECG image analysis using computer vision techniques to extract clinical features such as heart rate, rhythm irregularity, ST-segment deviations, QRS complex characteristics, and waveform abnormalities.
- The ECG analysis module generates annotated outputs and clinical findings, which are integrated with the prediction model to improve diagnostic reliability.
- The final output includes model-wise scores, ensemble confidence, risk classification, and detailed clinical insights, supporting effective and interpretable decisionmaking.

2) Bone Fracture Prediction

As seen in Fig 7 the bone fracture detection system uses a hybrid approach combining deep learning and computer vision techniques. It employs an ensemble of models with Grad-CAM for localization and integrates structural analysis methods to generate accurate and interpretable fracture predictions.

variance and enhance model stability.

- A weighted ensemble strategy is employed to combine outputs from individual models, assigning higher importance to medically pretrained models for improved reliability.
- Grad-CAM is integrated to generate activation heatmaps, enabling localization of fracture regions and providing visual explanations for model predictions.

- In addition to deep learning, advanced computer vision techniques are applied, including bone segmentation using thresholding and morphological operations, cortex continuity analysis to detect structural breaks, and Hough transform-based line detection for identifying fracture lines.

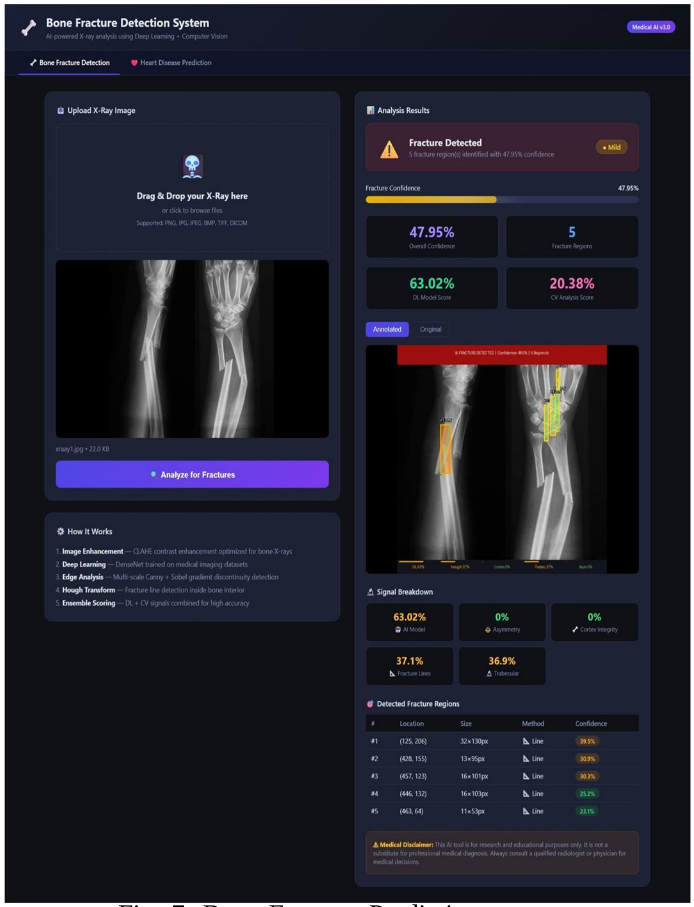

Fig. 7: Bone Fracture Prediction

- Further analysis includes trabecular texture disruption detection and intensity asymmetry analysis to capture internal and structural irregularities within the bone.
- A hybrid scoring mechanism combines deep learning predictions, Grad-CAM outputs, and computer vision analysis into a unified confidence score, improving overall detection accuracy.
- The system also incorporates multi-signal validation, where agreement between multiple detection methods increases the final confidence score.
- Detected fracture regions are highlighted using bounding boxes, along with confidence scores and region ranking for better visualization.
- The final output includes fracture detection status, confidence level, model-wise scores, and annotated visual overlays, ensuring both diagnostic accuracy and interpretability.

C. Fracture Detection Output Storage

The system includes a feature to store annotated fracture detection outputs for future reference and analysis. After processing X-ray images, the generated results with highlighted fracture regions and confidence scores are automatically saved in a dedicated folder as shown in Fig 8.

The feature enables easy retrieval, record maintenance, and supports clinical review.

The system outputs individual prediction scores as shown in Fig 9 from each model in the fracture detection ensemble, along with the final combined confidence score.

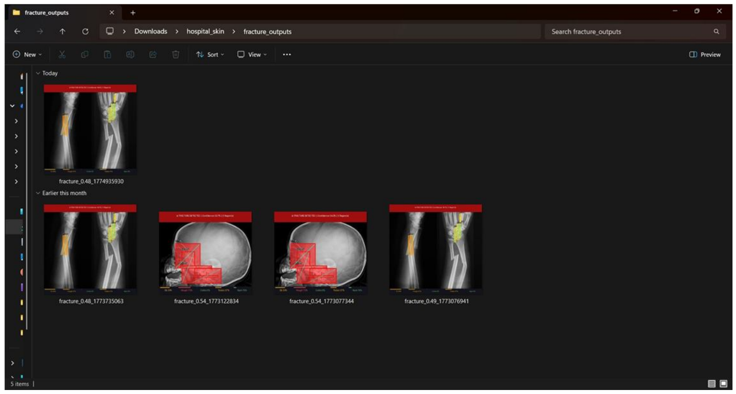

Fig. 8: Stored Fracture Detection Outputs

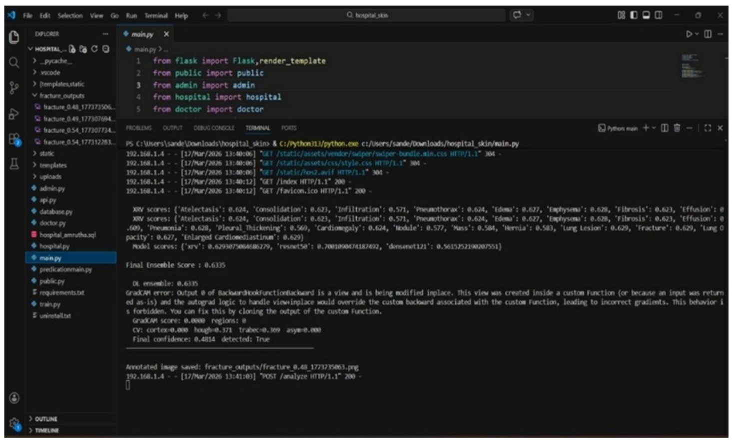

Fig. 9: Final Prediction Scores of Individual Models and Ensemble Output

V. CONCLUSION

In conclusion, the proposed HospAI system demonstrates the significant potential of integrating artificial intelligence with digital hospital management to enhance modern healthcare services. By combining AI-driven diagnostic modules for orthopedic fracture detection and cardiovascular risk prediction with a unified web and mobile platform, the system improves clinical efficiency, diagnostic accuracy, and patient accessibility. The use of ensemble learning, explainable AI techniques such as Grad-CAM, and hybrid computer vision approaches highlights the effectiveness of combining multiple methodologies for reliable and interpretable medical analysis. Despite these advancements, challenges remain in ensuring large-scale generalization, real-time clinical validation, and seamless integration with existing healthcare infrastructures. Addressing these limitations requires the development of more robust, scalable, and ethically guided AI systems that prioritize transparency, data security, and interoperability. Furthermore, incorporating multimodal data sources and continuous learning mechanisms can enhance system adaptability and long-term performance.Overall, HospAI represents a step toward intelligent, data-driven, and patient-centric healthcare systems. By integrating diagnostic intelligence with hospital workflows and mobile accessibility, the system contributes to improved decision-making, efficient resource management, and enhanced healthcare delivery. Future enhancements can further transform such platforms into essential tools for nextgeneration smart healthcare ecosystems.

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