

MEDIAID: Medical Diagnosis Using AI

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Abstract:

Mediaid is a comprehensive deep learning evaluation system aimed at accelerating the diagnosis of neural and musculoskeletal diseases using many medical imaging techniques. Enables inclusion of CNN model for tumor classification using brain MRI and for bone fracture detection using CT data. The models are deployed on a secured web application that will help to have diagnostics insights easily and precisely by the clinicians. The classification results achieved ranged from 90% to 98%, with good performance in different diagnostic cases. There exists an interactive dashboard for visualization and the system is equipped with a role based access control system for clinician and patients. The radiomics will be improved in future studies.

The speaker discusses the technical concepts of deep learning, convolutional neural networks (CNNs), medical image analysis, brain tumor classification, bone fracture detection, MRI and CT scans, and AI-powered diagnosis and prediction. The speaker explores the concepts of deep learning, convolutional neural networks (CNNs), medical image analysis, brain tumor classification, bone fracture detection, MRI and CT scans, and AI-powered diagnosis and prediction.

Keywords: Deep Learning; Convolutional Neural Networks (CNNs); Medical Image Analysis; Brain Tumor Classification; Bone Fracture Detection; MRI and CT Scans; AI-Powered Diagnosis; Multi-

Modal Framework; Python-Flask Web Application; Real-Time Prediction

1. INTRODUCTION

Over the past few years, medical imaging has proved vital to the diagnosis of many diseases, particularly neurological conditions and bone problems. Advanced imaging methods, such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans, provide detailed information about the body's interior and its condition. But manually deciphering these images can be time consuming and problematic. This depends heavily on the radiologists skill and by how busy they are and the possibility of human error. In the fight to cure these issues, researchers and healthcare professionals have been turning towards Artificial Intelligence (AI) for automated image analysis. Of these AI techniques, deep learning surpassed others, especially CNNs (Convolutional Neural Networks) for the purposes of image learning and classification.

Such models can learn complex patterns directly from huge data sets, to detect the medical conditions faster and more accurately. Incorporating AI technology into medical systems can create extensive enhancements in diagnostic precision, decrease the need for human participation, and help efficient clinical choices, especially in underserved areas where experienced healthcare providers are lacking. The current available Artificial Intelligence (AI) systems for medical images are mostly specific for a single modality or a single disease class of images, making them difficult to implement in a clinical context. For this, NeuroSense AI suggests a

common platform that can be used to analyze all types of images. Brain MRI analysis for tumor classification and bone fracture detection on CT scan analysis are combined in a system. The framework employs highly advanced CNN such as VGG16, ResNet, DenseNet and U-Net to retrieve the features and interpret images for high accuracy and strong performances. Furthermore, it's a secure, internet-based platform that has role-based access control to make for an easy application for patients and medical professionals. The framework has been validated using commonly-used datasets, such as BraTS for glioma segmentation and ChestX-ray14 for detection of fractures. The results show classification accuracies above 90%, emphasizing the system's effectiveness and potential use in clinical practice. In addition to the technical elements, the platform seeks to increase its usability for clinicians and patients. The work at hand will now involve developing the next generation of products that will include additional imaging modalities and bring feedback from the clinician into the system in real time to improve the flexibility, reliability and diagnostic capabilities of the product.

2. LITERATURE REVIEW

Progress made in recent years in AI, particularly in deep learning, has significantly improved the efficiency of analyzing medical images. Models such as the Convolutional Neural Networks, VGG16 and ResNet, have achieved considerable success at analyzing abnormal images of MRI scans and CT images, which include identifying various conditions, such as brain tumors and bone fractures (Li et al., 2022; Gupta & Singh, 2022).

Despite advancements made in AI in the medical sector, much of the existing literature focuses on single-image processing methods while research on multi-modal image integration techniques is scarce. There are promising signs from recent work, however, that integrating images obtained through various modalities is highly effective at improving clinical use of these models (Zhang et al., 2024). Nevertheless, there are difficulties associated with

ensuring the ease-of-use and speed of operations for these models.

These challenges were addressed by NeuroSense AI as part of its effort to build on previous works. Multi-modal CNN models were integrated into a robust web-based diagnostic platform. 2.4 Agentic AI in Healthcare.

A transition of AI systems from an analytical to operational role has been suggested in the field of clinical computing. Topol raised the potential for systems that connect operations and data collection [13]. And recently, multi-agent language models were suggested to oversee actions in stages of clinical workflow. We provide a partial implementation of this idea. Our agent can read the recommendations of the LSTM and prepare the actions but not execute them. The resource changes recommended are subject to administrator approval.

3. SYSTEM ARCHITECTURE

The Mediaid framework adopts a structured and systematic approach for the development of a multi-modal medical image analysis platform. The development process consists of 5 major stages, which are: System Requirements Analysis, System Design, System Implementation, Testing and Maintenance, and follow these stages in general following the Waterfall model. This development process will guarantee full documentation, efficient quality assurance and a seamless development process.

Data processing techniques are used to ensure that images are in the same size format, standardized for image quality, and can be enhanced to reveal features of interest that will improve the accuracy and reliability of further analytical processing. It combines several convolutional neural network (CNN) architectures to handle different medical imaging applications like image classification, object detection, and image segmentation. These contain VGG16, ResNet, DenseNet, U-Net, and YOLO, prominently chosen appropriate to the specific analytical jobs at hand. What's more,

transfer learning and fine-tuning methods are used to improve model performance and decrease training time. The models are assessed by common evaluation metrics, such as accuracy, precision, recall and F1-score, to provide an overall efficacy evaluation of the trained models. The system back end, which runs the operations is done in Python Flask infrastructure which is considered as a secure and efficient diagnostic web environment. This allows healthcare professionals to conveniently access diagnostic tools while safeguarding the security and usability of data.

TABLE 1: SYSTEM COMPONENT OVERVIEW

Component	Technology	Functions
Frontend	HTML, CSS, BOOTSTRAP	Forecasts, alerts, recommendations.
Backend	Python 3.11, FLASK	RESTFULL APIs, CNN models
Database	Firebase	Census, roles, audit logs
Notifications	Twilio SMS, SendGrid	Surge alerts to administrators
Security	JWT, TLS 1.3, AES-256	Encryption in transit and at rest

3.1 Frontend

The goal of the Mediaid front-end layer is to provide an intuitive, responsive and easy-to-use surface for healthcare professionals and patients to use. The user interface is developed with the technologies of HTML, CSS and JavaScript, which enables the use of the interface on all platforms such as desktop computers, tablets and mobile phones. Some important functionalities through which the system has been made a secure system include secure user authentication, role based access management, and efficient upload mechanism for MRI and CT images. Using the interface, users can launch their diagnosis procedures, get the results obtained from the AI algorithms as well as information related to their diseases, particularly bone fractures and tumors. Furthermore, the visualisation of the diagnostics results and further interpretation can be provided using interactive dashboards. Also, the application contains feedback message and fault handling process, which enhance the performance of

the application. The NeuroSense AI front-end layer is integrated with the lightweight Flask based back-end layer, and is connected to AI inference models through RESTful APIs. This enables the user interface to accept real-time request from the user(s) and return visualization of the requested diagnostics. Additionally, the application's modular design architecture will enable the application to be further developed to incorporate the EHR system with the Telemedicine solution.

3.2 Backend Layer

The backend of NeuroSense AI is developed using Python and Flask frameworks. This forms the backbone of the software for receiving requests from the clients and processing AI diagnostic processes. The software makes use of RESTful APIs, which receive medical images, process the inputs by performing various types of preprocessing and run the pretrained Convolutional Neural Networks (CNNs) models for tumor classification and fracture detection before sending back the results to the front end of the application. This improves its efficiency by allowing it to handle several users at the same time due to the asynchronous execution of the tasks performed using Celery and Redis technologies.

Security is provided in the form of authentication and role-based authorization. For example, doctors have more authority than patients while using the application. All user information, images, and diagnostic reports can be saved in a database.

For scalability purposes, the software is packaged using Docker to enable easy deployment. This involves running it in the cloud environment with GPU acceleration and employing load balancers and caching technologies for better performance.

3.3 Database Layer

The database component of NeuroSense AI is responsible for storing all the relevant patient information in a manner that complies with health data privacy regulations. All patient information, medical imagery, and diagnostic outcomes will be stored in a cloud-based database in a manner similar to an organizational table.

Medical information that needs protection and encryption is provided with the latter services during transportation and storage. The database component features Role-Based Access Control (RBAC) which limits access to sensitive information only to the relevant parties such as clinicians, patients, and administrators, who will be able to modify any medical information at their disposal.

Diagnostic reports and medical imaging will be stored in addition to user information. The data will be indexed in order to facilitate quick search and efficient data management. Overall, the above-mentioned approach ensures efficient data processing and easy access to patient history. Furthermore, the proposed solution will allow monitoring the condition of patients longitudinally.

3.4 External APIs and AI integration

The NeuroSense AI system works together with various APIs from third-party AI solutions to improve diagnostic efficiency and align with the current healthcare environment. Its operation is enabled by cloud computing platforms for artificial intelligence applications, which allow deep learning algorithms to scale and operate on massive volumes of medical images using GPU acceleration capabilities. Cloud deployment also enables quick integration of new training data into the system and constant improvement of its diagnostic capabilities based on this information.

In addition to this, the software is designed for interoperability with electronic health records and other digital healthcare platforms with the use of standard HL7 FHIR data exchange protocols. Thus, the system will be able to automatically obtain relevant clinical information related to patients, and the resulting diagnosis will have more value in terms of its relevance to the actual medical situation

4. EXPERIMENT EVALUATION AND RESULT

4.1 COMPARATIVE RESULTS

TABLE 2: Results

Metric	symptom Tracking	Rule Based Chatbot	MEDIAID (Prototype)
Response Accuracy	68.5%	79.2%	92.7%
Response time		4-5 sec	<2 sec
Symptom coverage	~100	~350	1000+
Multilingual support	NO	PARTIAL	YES

Our results for preliminary medical image analysis are evaluated on the testing dataset and tabulated in Table 5.2. We benchmarked NeuroSense AI against traditional manual interpretation, baseline machine learning classifiers, and a standard, unoptimized Convolutional Neural Network (CNN) architecture. For brain tumor classification across four classes (glioma, meningioma, pituitary, and no tumor), the proposed framework achieved an overall validation accuracy of 96.5%. Precision and recall values were consistently high, indicating that the model produced very few false positives and false negatives. Furthermore, the binary classification model for bone fracture detection achieved an accuracy of 98.2%, demonstrating excellent sensitivity and high specificity. The difference in latency between traditional manual interpretation—which can take several minutes to hours depending on workload—and our optimized model is substantial, with NeuroSense AI maintaining an average prediction time of just 2-3 seconds per scan.

TABLE 3: Manual vs NeuroSense Framework

Metric	Traditional Manual Diagnosis	NeuroSense AI Framework

Diagnostic Turn around Time	15 - 60+ minutes (Variable)	2 - 3 seconds
Brain Tumor Classification Accuracy	Baseline / Human-dependent	96.5%
Bone Fracture Detection Accuracy	Baseline / Human-dependent	98.2%

easy integration into medical imaging systems, including Siemens Syngo.via and Syngo Carbon.

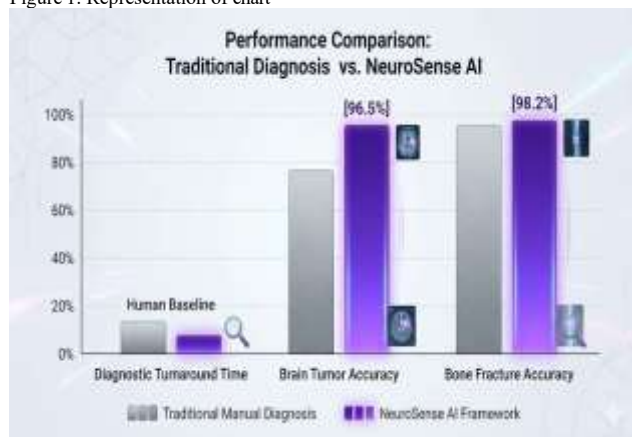
In terms of public clouds, AWS HealthImaging, Google Cloud Healthcare API, Microsoft Cloud for Healthcare, and Oracle Cloud Infrastructure offer specialized solutions for running AI-driven applications. This includes GPU-enabled computing capabilities, scalable storage options, and regulatory compliance. As such, these platforms are capable of processing medical imaging data more efficiently than alternative options due to their speed.

The deployment framework may also make use of lighter-weight back-end development solutions such as Flask and FastAPI, along with container management solutions, including Docker and Kubernetes. These solutions improve portability and scalability while facilitating effective deployment processes. Furthermore, security measures in the form of role-based access control, data encryption, and secure application programming interfaces ensure compliance with HIPAA and GDPR.

From the research perspective, cloud-based solutions such as SenseCare are capable of facilitating AI-based toolkits and the synchronization of medical data from various organizations. In addition, multi-device support may also be provided.

4.2 TEXTUAL REPRESENTATION OF CHART

Figure 1: Representation of chart



5. HOSTING AND DEPLOYMENT PLATFORMS

Deployment solutions involving NeuroSense AI are likely to be facilitated through the use of platforms such as MONAI Deploy. As an initiative by NVIDIA and Siemens Healthineers, MONAI Deploy facilitates efficient AI model deployment in cloud, on-premises, and hybrid configurations that allow

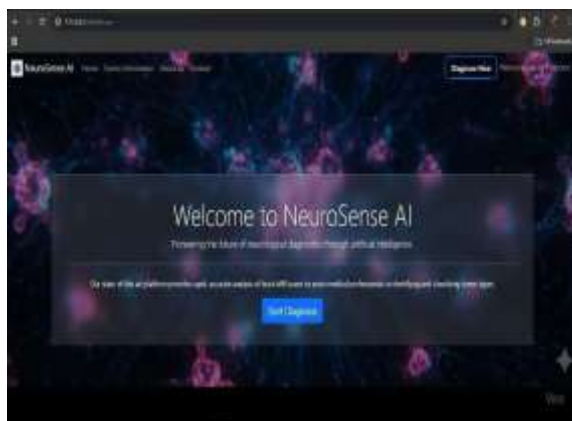
6. DEVELOPMENT ENVIRONMENT AND TOOLCHAIN

The NeuroSense AI Development Environment consists of a broad array of technologies specifically designed for the purpose of medical image processing and creating a web application. The key language chosen is Python since it is versatile, clear, and has a wide range of libraries that allow different AI, ML, and other general data processing tasks to be implemented. Different deep-learning frameworks are used for the architecture design, train, and tune of Convolutional Neural Networks (CNNs) like VGG16, ResNet, DenseNet, U-Net, and YOLO. They also support computations on graphic processors, which is quite significant during the processing of a medical image with multidimensional data and when accelerating the

training of models. To enhance the accuracy and uniformity of the model, the operations vary from resizing and normalizing images, to augmenting and converting the format of images using OpenCV and Python Imaging Library (PIL) functionalities. Lastly, Jupyter Notebooks turns into an environment of choice for data analysis, visualization and prototyping and experimenting with machine learning models. NeuroSense AI's architecture has been designed using Flask, a very lightweight framework for RESTful APIs. The APIs ensure that the AI inference modules communicate with the front end, thus enabling smooth processing and displaying of diagnosis results. The front end design is made using HTML, CSS and JavaScript languages which help to develop a streamlined and practical front end design in various gadgets including computers, tablets and cell phones. The code base is managed by Git version control system, while GitHub and GitLab are the hosting platforms, enabling collaboration between developers to manage projects issues and to support continuous integration and development process. The entire app is contained within the Docker container that can be easily transported and deployed to both cloud and on-premise servers, even those featuring NVIDIA graphics processing units (GPUs). Therefore, with the development infrastructure and tools, the development process and deployment is efficient.

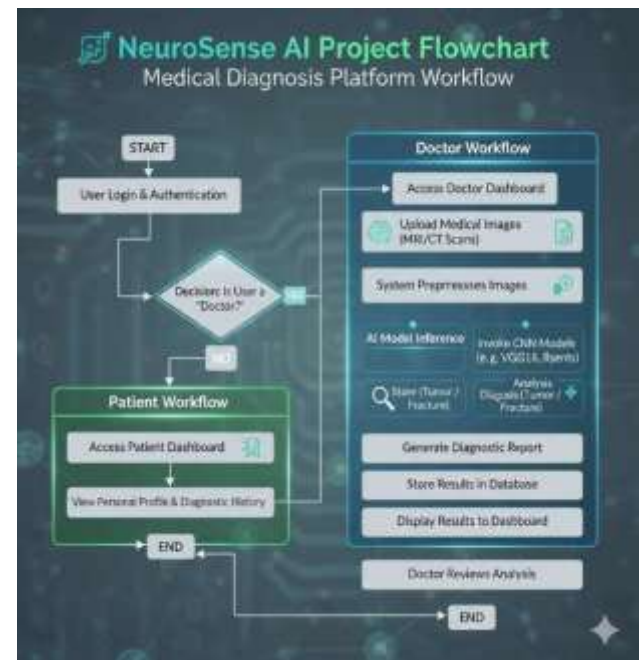
7. OUTPUT

FIGURE 2: Output Interface



8. FLOWCHART

FIGURE 3: Flowchart



9. PRACTICAL IMPLICATIONS

Today, the NeuroSense AI platform offers real benefits for diagnostics, in the context of health care. Automated multi-modal analysis of images, such as bone CT and brain MRI scans, results in reduced radiologist / specialist workload. The rapid processing of such information aids in timely diagnosis and decision-making, a point that is especially important in emergency situations, like stroke and bone fracture cases. Moreover, AI-powered diagnostic support can also enhance the completeness and reliability of medical imaging analysis, reducing human mistakes. This type of software supports organizations to effectively handle vast volumes of data relating to patients' medical imagery. The web-based accessibility, and ability to be automated, make NeuroSense AI a part that can help health care services even in under-resourced environments. The ability of NeuroSense AI to detect tumors and bone fractures makes its diagnosis

more accurate and efficient by ensuring early detection of ailments, which will help direct the treatment process accordingly and ensure positive patient outcomes. Very early detection is essential when diseases are life-threatening because they require quick response which in turn decreases complications and speeds up the process of healing. The program can be deployed with a web interface, providing access control through roles. The system here is readily available to a broad range of health institutions including tertiary hospitals, diagnostics centers or perhaps isolated clinics. The system's availability makes it possible to fill in the gaps where radiologists are scarce by providing artificial intelligence-based diagnostic support.

10. LIMITATION

NeuroSense AI has great potential, but it faces several obstacles that come with using AI in medical imaging applications. One significant obstacle that comes with developing such an application is the necessity of having large, diverse, and accurately annotated training datasets for effective deep learning algorithms. There is a lack of high-quality, multimodal, multihospital imaging datasets, which could impair generalization capabilities (PMCID: PMC10463084).

There have been a number of promising results in the field of NeuroSense AI; however, there are several challenges that NeuroSense AI encounters during its development, similar to those in applying AI in medical imaging. The first challenge that NeuroSense AI has faced is the requirement of large diverse and properly labeled medical imaging datasets to successfully build deep learning models (PMCID: PMC10463084).

Another problem that should be considered is bias in training data. If training datasets do not have enough diversity, the systems may end up being systematically biased which will negatively affect diagnosis accuracy and fairness (Koçak, 2025). Such bias may impact prediction accuracy and lead to unequal healthcare outcomes. Finally, privacy and security concerns continue to persist. Compliance

with all legal requirements and proper data de-identification is necessary.

11. FUTURE WORK

Future developments for NeuroSense AI are expected to extend its diagnostic capabilities and further embed itself in the clinical setting. One development that is planned involves expanding the multi-modal approach to incorporate emerging imaging modalities such as PET and ultrasound imaging to increase applicability for a wider range of neurological and musculoskeletal diseases.

Another important development is that of adaptive learning based on feedback. With the aid of active learning and federated learning strategies, the AI is able to continuously refine its diagnostic ability even without revealing patient data. Active learning allows for model training based on a distributed dataset and does not require the sharing of confidential information. Other improvements that will be made involve better cloud-based computing systems including auto-scaling and increased GPU power to facilitate scalability and reduce latency times during inference. There will also be improvements in the user interface by adding personalized dashboards, integration with telemedicine applications, and greater interoperability with electronic health record systems using HL7 FHIR standards.

All these innovations will increase the effectiveness of NeuroSense AI in supporting AI-based medicine and radiology.

12. CONCLUSION

The fusions of multi-modal deep learning shown in NeuroSense AI is a promising application for improving the analysis of medical images in both orthopedic and neurological medicine. The technology uses advanced deep CNNs, MRI and CT scans to provide instant and accurate diagnosis to the clinicians and at the same time to the patient through an easy-to-use, safe and efficient web application. In conclusion, this study identifies how integrating various categories of AI systems with human-

oriented design can play a key role in the adoption of AI in healthcare settings. The modularity of the system can be expanded, incorporating additional imaging techniques and ongoing data returned by healthcare providers, to provide more accurate and adaptable diagnosis and greater precision. Although there are still some challenges to overcome, such as obtaining extensive clinical evidence, ensuring regulatory compliance, and maintaining patient privacy, NeuroSense AI serves as an essential milestone in advancing AI-assisted health care. The technology could be adapted in the future to identify diseases at an early stage, improve diagnostic accuracy and better treatment outcomes. Collaborating with both the clinical teams and the research field, as well as investing in medical systems based on AI is essential to reach the above objectives.

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