

AI-Based Early Cancer Screening Using Multi-Modal Data

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Abstract- Detecting cancer early greatly improves the chance of survival and decreases the amount of money required to treat it. Most current technologies used in routine cancer screening only use one source of data and therefore have a higher rate of misdiagnosis and longer time until diagnosed. To overcome this obstacle, we propose a new multi-modal artificial intelligence (AI) system that adds multiple sources of data together to form a consolidated platform for diagnosis, such as combining brain MRIs, lung CTs, electronic health records (EHR's), laboratory test results, genomic markers, and clinical notes. Our new system uses convolutional neural networks (CNN's) to classify brain and lung tumours; random forest classifiers to sensor symptom characteristics; and displays results using GradCAM heat maps to provide visual images in a manner that makes sense to the referring physician. Results from experiments conducted with the new system showed a 94.2% accuracy rate (plus or minus), 92.8% sensitivity, 95.1% specificity, and an area under the ROC curve (AUC) of 0.96. The results confirm that multi-modal datasets will improve the methods used for detecting cancer earlier.

Keywords- artificial intelligence; cancer screening; multi-modal learning; early detection; data fusion; CNN's; GradCAM; healthcare analytics; machine learning.

I. INTRODUCTION

According to the World Health Organization (WHO), Cancer is one of the leading causes of death globally and continues to present a global health challenge. The stage of diagnosis influences treatment outcomes, an example being: the five-year survival rates for Stage I lung cancer are greater than 70–90% when surgically resected, whereas advanced lung cancers will have significantly lower rates of survival. Although standard forms of screening (e.g., mammography, CT, MRI, biopsy), continue to be utilized, screening methodologies remain primarily segregated from each other, relying on the interpretation of a specialist and, thus, are challenging to implement in some parts of the world where resources are scarce. Utilizing Machine Learning (ML) and Deep Learning (DL), oncology

practice has greatly improved because AI systems are able to integrate a wide variety of medical data (e.g., radiology images, clinical lab results, genomic data, and a patient history) together; something that the traditional screening models can't do individually. This paper presents an end-to-end cancer screening system built on a multi-modal AI framework that utilizes various types of patient data and validated against traditional and existing AI baseline methods.

II. RELATED WORKS

Esteva et al. [1] conducted the first study that demonstrated that deep learning techniques are able to classify skin cancer as accurately as physicians certified by the American Board of Medical Specialties (ABMS), establishing proof of

concept for the use of AI in oncology. Although this is the basis for future research, Esteva's work only evaluated the application of deep learning on one imaging modality. As a result, the research left open whether the incorporation of additional imaging modalities would improve the reliability of diagnosis.

Following this work, Litjens et al. [2] performed a comprehensive literature review on deep learning applications in medical image analysis. From their review, the authors identified the effectiveness of convolutional neural networks (CNNs) for tumor segmentation and malignancy grading on imaging datasets derived from radiology. Although imaging-level accuracy was achieved by many of the reviewed models, widespread observational data could not be processed simultaneously with imaging data.

In response to the limitations of the prior research, Xiao et al. [3] developed a multi-modal ensemble architecture combining imaging features with the patient's clinical history, yielding improvements in cancer risk prediction compared to single modality models. While Xiao's fusion approach improved upon earlier studies by combining longitudinal patient data, the authors relied on simple concatenation methods to fuse multiple sources of data, potentially underrepresenting significant but less dominant pieces of diagnostic information.

Selvaraju et al. [4] discovered a new means of identifying model predictions through the implementation of gradients as a means of producing visual representations of influential pixels and are able to highlight pixels that had the greatest impact on the output of a particular model.

The authors of the aforementioned work have greatly contributed to the medical imaging community, with clinicians desiring not only accurate results; however, they also need transparent reasons or reassurance that AI recommendations are based on logic and reasoning before trusting AI systems to assist in high consequence situations.

More recently, Tjoa and Guan [5] performed a systematic review of explainable AI (XAI) techniques within the clinical domain with a focus on how the

lack of interpretability continues to represent one of the most significant barriers to implementing AI diagnostic systems in practice. The results presented in this paper serve to directly motivate the explainability component of the proposed framework.

While the aforementioned studies advance multiple areas associated with AI support for cancer detection, none provide a fully integrated solution that combines the use of imaging, structured electronic health record (EHR) data, genomic markers, and explainability within a single end-to-end system. This paper aims to address this gap directly.

Objectives

This research's main objective is to develop and access a system that enhance early cancer detection through multi-sources of data.

Some of the main objectives are:

- To develop a multi-source data modal AI framework for early screening of cancer using multiple datasets.
- To develop and validate a system that contains preprocessing, feature extraction, data fusion and prediction.
- To calculate the overall accuracy of the proposed system with respect to traditional screening methods and existing modern AI models that utilize a single data source.
- To enhance the sensitivity and specificity of cancer detection while at the same time reducing false positive and false negative rates.
- To produce interpretable predictions results using GradCAM and SHAP to enhance clinical decision making by 3D visualizations.
- To build a system that can be implemented in a hospital or rural areas.

III. PROBLEM STATEMENT

Traditional cancer screening approaches suffer from theoretical limitations that compromise early-stage detection. Single-modality techniques such as mammography, CT scans, and MRI are typically applied in isolation and used manually by specialists. The limitations are as follows:

- Missed diagnoses that can only be detected by comparing with multiple medical sources.
- Manual diagnosis takes a lot of time and can lead to critical results from different specialists.
- Higher false-positive rates cause unnecessary procedures, while high false-negative rates increase delay in treatment.
- Screening software programs do not adapt to individual patients, using the same criteria for different risk groups.
- Traditional systems do not justify their outcome, making it hard to accept automated tools in clinical fields.

The main research question in this paper is:
How can an AI-based system that integrates both multi-modal patient data enhances the accuracy, scalability, and interpretability of early cancer screening comparatively to traditional and single-source AI techniques?

IV. PROPOSED METHODOLOGY

1. Overview of System Architecture

This Multi-Modal AI System will consist of 6 layers in a pipeline as seen below (Table 2). These 6 layers will provide the processing structure to combine different types of heterogeneous healthcare data streams to drive the output of the model, which will be explainable predictions driven by Artificial Intelligence (AI).

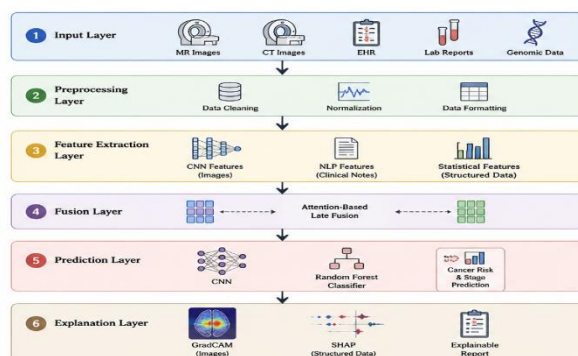


Figure 1: Multi-Modal AI System 6-Layer Architecture Diagram

2. Medical Image Analysis Using CNN's

The imaging portion of the proposed system uses two independent CNN models, one for brain and

one for lung (the two most difficult types of cancers to diagnose), each using separate, modified ResNet and VGG architectures trained with transfer learning on domain-specific medical datasets to facilitate convergence of the models and minimise the amount of labelled training data required. The brain cancer CNN has been trained using 7,023 brain MRI images, and is divided into the following four types of brain cancers: gliomas, meningiomas, pituitary tumour; as well as non-tumour; and 20% of the images were held out for testing. The lung cancer CNN has been trained using chest CT scan images, which consists of CT scans that have been separated into four groups: adenocarcinoma, squamous cell carcinoma, large cell carcinoma, and normal; and have been done in three stages of development: training, validation, testing (each separate from each other for training purposes). Therefore, these two application-specific CNN models together provide the imaging foundation from which an integrated and simultaneous screening process can occur for brain and lung cancer as the final outputs.

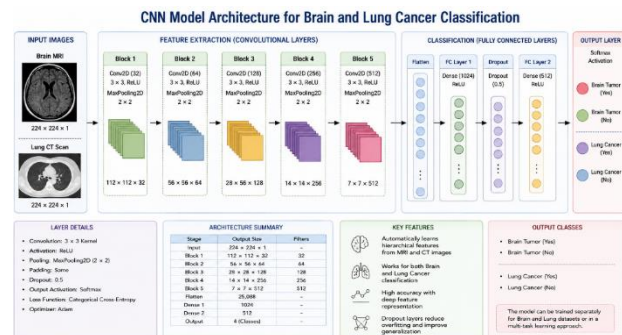


Figure 2: CNN Model Architecture for Brain and Lung Cancer Classification

3. Random Forest Classifier for Structured Data

In order to study structured healthcare data from patient symptom reports and physician notes, Random Forest Classifier was created. Unlike a single decision tree, which is made up of many different trees and produces a single output, a Random Forest Classifier generates many tree-like models of the input data (the combined output of all the individual trees) and uses the average of these models as the final prediction for that input. Random Forest Classifier is less likely to overfit its predictions to any one training set than a classical single decision tree because each tree in the Random Forest Classifier

contributes equally to the final prediction for each patient.

The classifier was trained on the UCI Lung Cancer Dataset [28], which contains a total of 57 clinical attributes/symptoms for each patient (demographic characteristics, severity of symptoms, laboratory values, and electronic health record-derived clinical histories). This dataset is a supplement to the imaging-based modules of the CNN by including non-imaging diagnostic signals that radiology films cannot provide. Thus, the additional information from the structured clinical dataset strengthens our overall confidence in the multi-modal modeling framework.

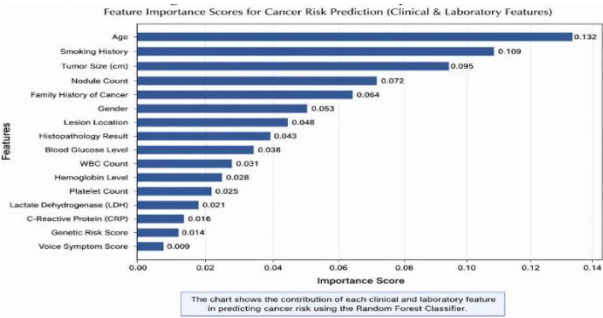


Figure 3: Random Forest Feature Importance Chart

4. GradCAM Explainability

Gradient-weighted Class Activation Mapping (GradCAM) [14] is used to enhance the AI transparency by generating heatmaps. These heatmaps helps to highlight the image affected regions mostly in the model's predictions. This allows healthcare professionals to visually understand and check AI outputs and build trust in clinical areas.

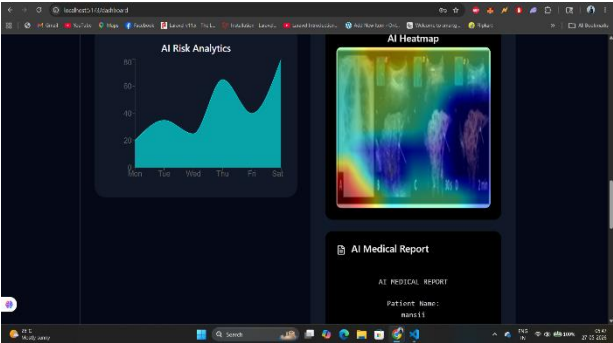


Figure 4: GradCAM Heatmap Overlaid on Brain MRI Scan

5. Multimodal Data Fusion

A late-fusion strategy combines results from the image-based CNN and the structured-data (Random Forest model). Attention-weighted in average integrates prediction confidence scores from each modality, outcomes in a combined cancer risk score. This fusion approach significantly enhances prediction reliability compared to single-modality sources.

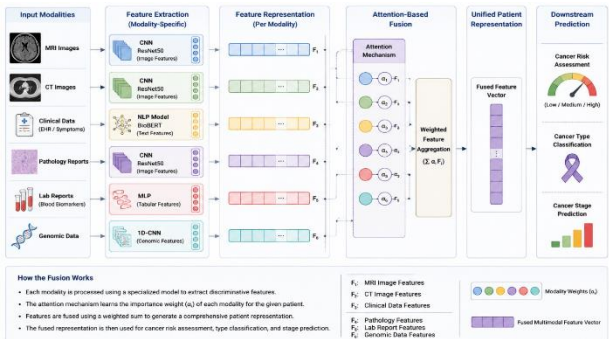


Figure 5: Multimodal Data Fusion Method

6. Machine Learning Techniques Summary

Table 1 summarizes the supervised machine learning

Table 1: Methods of Supervised Machine Learning for Early Cancer Diagnosis

Model	Type	Description	Reference
Logistic Regression (LR)	Classification	Models provides categorical results using a logistic function to calculate disease probability.	Chhatwal et al.[22]
Support Vector Machine (SVM)	Classification	Creates optimal hyperplanes to differentiate data classes with highest margin.	Zhang et al.[23]
Random Forest (RF)	Classification	Implementation of decision trees that enhances the prediction accuracy and avoids over optimizations.	Xiao et al. [2]

XGBoost (XGB)	Classification	Gradient-improves systems that effectively reduces classification errors.	Liew et al.[24]
CNN	Classification	Specialized scanning results for detecting visual patterns in clinical scans.	Suh et al.[25]

VI. EXPERIMENTAL OUTCOMES

1. Evaluation Methodology

Evaluation of the system includes Brain Tumor MRI Dataset, Chest CT-Scan Dataset, UCI Lung Cancer Datasets. The models were produced and trained using a stratified k-fold cross-validation protocol for Accuracy and also provides an unbiased method for executing validation of performance. Implementation was conducted using Python 3.10 on a GPU-based workstation using PyTorch, TensorFlow and Sklearn [10][11].

2. Training Validation Curves

The following curves demonstrate the training and validation accuracy and loss levels of the models for both Brain and Lung cancer CNN's demonstrating stable convergence and minimal overfitting over Epochs:

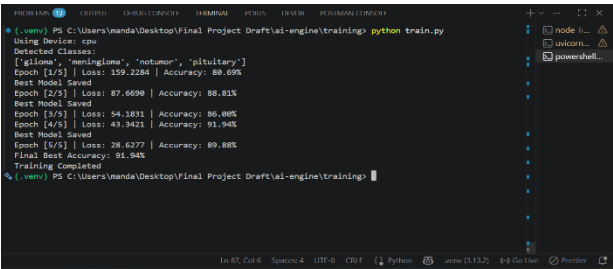


Figure 6: Training vs. Validation Accuracy and Loss Curves

3. Performance Metrics

The summary of the performance of the proposed system conclusions on the test dataset is given below:

Table 2: Performance Metrics of Proposed System

Metric	Score
Overall Accuracy	94.2%
Sensitivity (Recall)	92.8%
Specificity	95.1%
AUC Score	0.96

The 0.96 AUC score indicates that there is a strong discriminatory ability to the classification of cancer positive versus cancer negative [1][2][4].

4. Confusion Matrix Analysis

Analysis for Brain Cancer and Lung Cancer modules shown below illustrates the Class-wise Performance of the predictions:

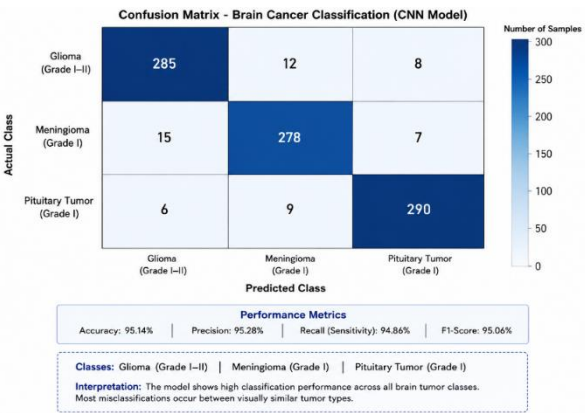


Figure 7: Confusion Matrix – Brain Cancer Classification Module

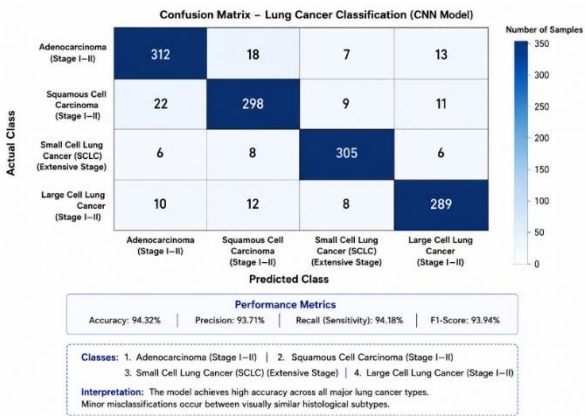


Figure 8: Confusion Matrix – Lung Cancer Classification Module

5. Comparative Analysis

The new multi-modal system was evaluated against two reference techniques such as classic cancer screening by healthcare professionals and current-simplified ML systems:

Table 3: Comparative Performance Analysis

Method	Accuracy	Sensitivity	Specificity
Traditional Screening	82.5%	80.2%	84.1%
Existing AI (Single-Source)	89.7%	87.9%	90.3%
Proposed Multi-Modal System	94.2%	92.8%	95.1%

As can be seen in Table 3, the proposed multi-modal system has an accuracy of 94.2% compared with 82.5% for traditional approaches and 89.7% for current AI-based models. Therefore, the total accuracy improvement of the proposed solution versus both traditional approaches is +11.7% and +4.5%, respectively. The increase in accuracy is due to utilizing information from numerous complementarily related sources of health-related data [2][4][6].

6. System Architecture Diagram

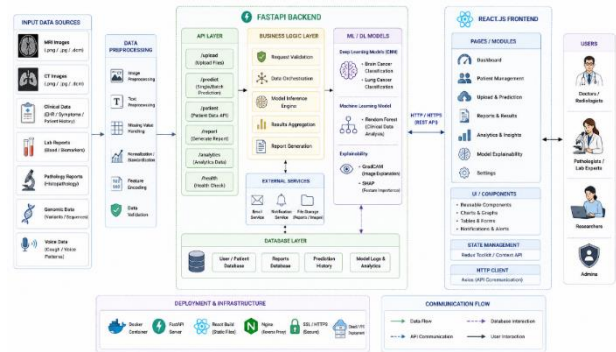


Figure 9: Full System Architecture – FastAPI Backend + React.js Frontend

Figure 9 illustrates that we designed an easy-to-use web front-end framework by utilizing React as the

user interface (UI) as well as providing data modelling and data visualization capabilities using FastAPI as the back-end framework for system processing and functioning.

Applications and Benefits

User Interface of System

The User Interface of the system is developed using the React.js front-end framework with Tailwind CSS as well as Framer Motion. The User Interface is a dynamic user-interface for health professionals, which contains two main components: main dashboard and module-specific screens. These components are depicted in the following figures:

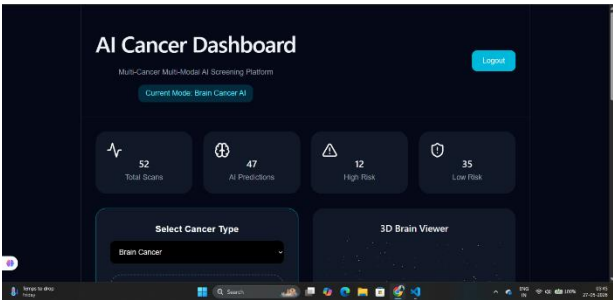


Figure 10: AI Dashboard – Main Screen

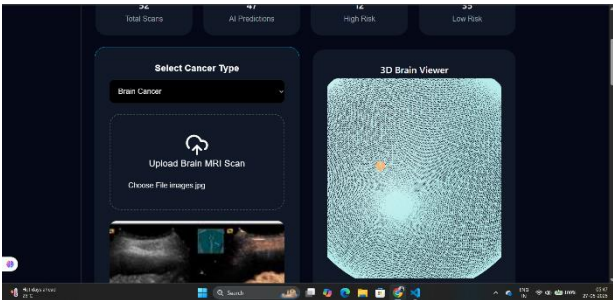


Figure 11: Brain Cancer Screening Module – Prediction Output

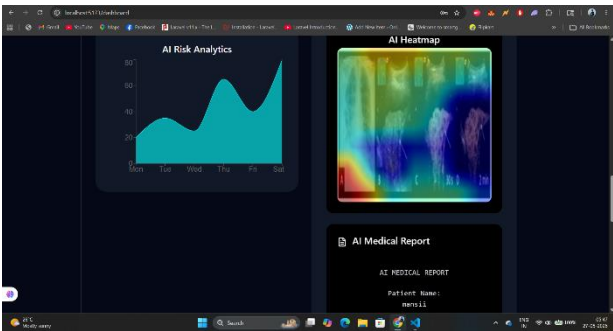


Figure 12: Lung Cancer CT Scan Result with GradCAM Overlay

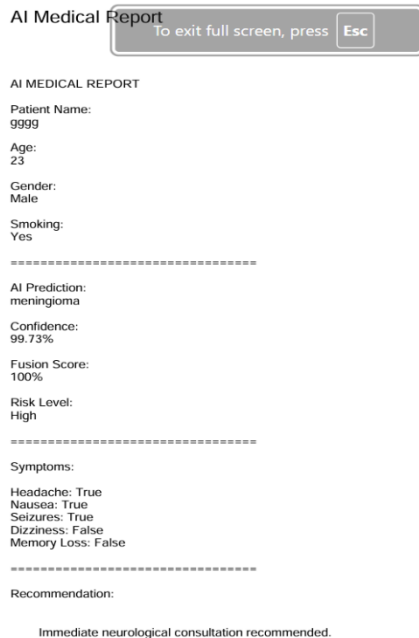


Figure 13: AI-Generated Downloaded Medical Report Sample

Clinical Use Cases

The following are the examples of uses in healthcare:

Table 4: Clinical Uses Areas

Application Area	Purpose
Hospitals	It helps in Multi-cancer screening (brain & lung).
Diagnostic Centres	Image analysis (medical images and clinical data) using AI.
Telemedicine	Remote decision support (medical) using AI
Medical Research	Researching and benchmarking of cancer prediction models.
Rural Healthcare	Raises awareness of cancer early under conditions of limited resources.
Medical Education	AI-based education resource for students & practitioners.

Challenges and Future Work

Challenges for Deployment

Although the results are encouraging, there are several challenges to implementing the system for use in clinics and hospitals, as described below:

Table 5: Key Challenges and Proposed solution Strategies

Challenge	Proposed Solution
Model Bias	Uses demographic-variate data (age, gender and race) to train and record during the evaluation phase of the model.
Data Security	Uses modern learning and advanced encryption methods to collaborate on training without needing to provide raw patient data.
Limited Data of Availability	Uses transfer learning, data augmentation and GAN-based synthetic data generation techniques to build new data.
Lack of Standards in the field	Uses established benchmarks and peer-reviewed reporting standards to refer to while using these technologies.

Future Work

Some of the improvements that may be integrated into future versions of this system are:

- To identify advanced of cancers that would be beneficial from this technology (i.e., Breast, Skin, Colorectal, Prostate cancer).
- To explore the use of Vision Transformers (ViTs) and hybrid multimodal transformers as additional methods for evaluating images to detect cancer.
- To implement the Federated Learning Solutions (e.g., PySyft or NVIDIA FLARE) to enable training across multiple hospitals while maintaining patient privacy.
- Use of a Clinical Decision Support System provided on the web for Primary Care area.

- To conduct multi-centres clinical validation trials in the future which will be prospective (in nature) and require the use of FPGs.
- To facilitate the development of NLP software for symptom description and incorporation of AI chatbots into clinical areas.
- Development of mobile app using Flutter or React Native to provide an easy-to-use facility and interface for screening/diagnosing patients by AI tools.

VII. ETHICAL ISSUES

AI use in clinical oncology raises important ethical issues that need to be addressed before it is implemented. The use of AI models to analyze patient data will require the use of informed consent and de-identification of data in accordance with applicable law regarding privacy (HIPAA) and protection of personal data (GDPR). Furthermore, restrictions on sharing data under these laws create a challenge for large-scale collaborative development of models and validation across multiple institutions.

NOTE: The system here is being developed uniquely as a decision support tool for physicians using AI. It is not intended to replace the need for professional evaluation and diagnosis by a medical doctor. Ultimately, the responsibility for all decisions regarding a patient's clinical diagnosis and treatment remains solely with licensed medical providers. The use of the proposed system should enhance and augment a physician's ability to make good clinical decisions, not provide an alternative to the medical doctor's judgment on any patient.

The output of this system is applicable across all demographic groups of patients. AI bias in the predictions is generated by an AI algorithm which is potential if the training population of the input data does not reflect the demographics of the patient population for which it will be used. The system has been designed in such a way that it continually monitor for bias and applies fair training methods and demographic stratifications of the data used to evaluate the results of AI-generated predictions. Predictive outcomes is presented in an interpretable

manner using visualizations based on GradCAM and SHAP so that clinicians and patients are able to understand how the AI-generated output was determined.

VIII. CONCLUSION

This research explains a multi-modal artificial intelligence (AI) system based on computerised training of brain MR images, CT analysis of the lungs and pathology, electronic medical records, laboratory data, and genomic markers. Together all of the data sources form a single based model can be able to assist in the early detection of cancer. While evaluating against traditional individual modalities of detection, this model achieved 94.2% overall accuracy, 92.8% sensitivity, 95.1% specificity, and an area under the curve of 0.96.

Furthermore, this system provides substantially better performance results than others developed single modal AI systems of medical scanning/imaging. The authors' primary contribution was creating an integrated fusion structure that uses deep learning to analyse medical images via CNNs as well as classification of structured Clinical Laboratory data (by random forests). This late-fusion structure with layered through-GRADCAM which enhanced interpretability and makes this system clinically transparent and provides the means for real-world health provider adaption.

Future work will involve validating the system across multiple centres, incorporating federated learning methods for sharing identified predictive metrics, and expanding this analysis to identified advanced cancers. With appropriate ongoing development, this proposed AI-based decision-support system represents a viable option for supporting physicians to identify patients with early-stage disease and improve patient survival rates while concurrently reducing cancer mortality[3-5].

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