IJARR, 7(5), 2022; 77-85

International Journal of Advanced Research and Review

www.ijarr.org

Deep Learning for Early Cancer Detection: A Multi-Modal Approach Integrating Radiomics and Genomics

Author 1
Dedeepya Sai Gondi, Lead Engineer Department
sai.gondi@ieee.org
Author 2
Bandaru Vamsi krishna Reddy, Lead Analyst
bvkrba@gmail.com
Author 3
Srinivas Reddy Bandaru, Doctor, Department of Oncology
drsrinivasreddy21@gmail.com

***Abstract*—This research develops a fresh deep learning architecture that joins radiomics with genomics to achieve better cancer finding together with classification functionalities. The research combines convolutional neural networks (CNNs) together with transformer-based architectures for image processing of radiology pictures while adopting graph neural networks (GNNs) with autoencoders to analyze genomic sequencing information. The developed multi-modal fusion model processed TCGA plus TCIA public dataset information to reach 92.7% accuracy rates when predicting early-stage cancers throughout various types.**

Keywords— Deep Learning, Early Cancer Detection, Radiomics, Genomics, Multi-Modal Fusion, Medical Imaging, Precision Medicine.

I. INTRODUCTION

The annual global death toll surpasses millions due to the significant health issue known as cancer. The early discovery of cancer leads to better treatment results which enhance survival statistics for patients. Three main diagnostic procedures such as histopathology, imaging and biomarker-based screening experience several problems including inconsistent results, late-stage discovery and subjective interpretation difficulty [2-6].

Medical scans such as CT along with MRI and PET fall under the purview of radiomics since this field extracts complex quantitative imaging features at high dimensions. The adoption of these features helps physicians evaluate tumors more precisely through their capability to reveal both diverse biological cell types and ecological environment elements. The analysis of genetic mutations alongside gene expression markers and other biomarkers which represent cancer development takes place through genomics [13-15].

The diagnosis of cancer currently uses radiomics and genomics technologies separately from each other at present. The combination of these two modalities under deep learning presents the chance to construct an advanced system for early cancer detection which offers complete and accurate results. The combination of imaging data with molecular data through deep learning produces an effective method for detecting early-stage cancer at a higher level of accuracy [7-8].

Novelty and Contribution

The proposed research creates a distinct multi-modal deep learning platform which incorporates radiomics information with genomic data for early cancer discovery enhancements. This study makes multiple essential contributions which consist of:

A. Multi-Modal Fusion for Cancer Detection

The research implements a diagnostic integration of both radiomics and genomics that utilizes their unique complementary data for better accuracy. When specializing data from separate assets the approach generates extensive knowledge about molecular cancer features together with phenotypic measurements.

B. Advanced Deep Learning Architectures

The CNN architecture handles imaging data sets to detect complex tumor patterns embedded in radiomic inputs. The DNN system specializes in genomic data analysis to detect vital cancer-attributed genetic indicators. Through effective fusion of both modalities a model achieves its best performance in cancer classification [10].

C. Superior Diagnostic Accuracy and Robustness

The proposed model outperforms unimodal approaches in terms of classification accuracy, sensitivity, and specificity. Research data show better detection ability between malignant and benign tissue occurrences particularly targeting early-stage cancers [11-12].

D. Clinical Relevance and Precision Medicine Impact

The combination of radiomic data analysis together with genomic data collection enables personalized cancer diagnosis strategies that help develop treatment plans. The automated system decreases variability between readers and improves diagnostic decision-making ability for medical practitioners who specialize in oncology.

E. Addressing Data Heterogeneity

The introduced alignment strategy deals with data inconsistencies between genomic information and imaging data. The method delivers consistent performance results regardless of the types of data records and patient groups. This research establishes a connection between radiomics and genomics through deep learning procedures that leads to the development of a better early cancer detection system.

II. RELATED WORKS

The field of medical diagnostics has experienced fundamental changes because of deep learning technology that performs better in cancer early detection. Artificial intelligence receives analysis through multiple studies which examine the use of its capabilities for medical images and genomic data and clinical parameters to enhance diagnostic precision. The research discussion reviews three major topics: radiomics-based detection of cancers, genomics-driven approaches as well as multi-modal deep learning frameworks.

A. Radiomics-Based Cancer Detection

In 2021 J. Smith et al. [1] Introduce the medical imaging features extracted by the process of radiomics has become a common approach in cancer detection and prognosis and treatment outcome prediction. Researchers built convolutional neural networks after deep learning models developed which processed medical imaging data obtained from computed tomography (CT) and magnetic resonance imaging (MRI) and positron emission tomography (PET). The models show ability to make benign from malignant segregation and can classify tumor types while forecasting how tumors will advance. Yet radiomics has restricted capabilities because imaging protocols differ too much while scan quality can change substantially and the system does not track molecular characteristics of tumors.

B. Genomics-Based Cancer Detection

In 2021 P. Turner et al. [9] Introduce the deep learning algorithms process genomic information regarding expressions and changes in DNA to determine tumor type and forecast healthcare results in patients. Rephrase the following sentence. RNNs and DNNs process sequencing information to discover genetic markers responsible for cancer progression. Research investigations have implemented attention mechanisms which support the identification of essential genomic features that play a role in cancer diagnosis. The valuable information within genomic data should be handled with caution because the data contains multiple flaws and dimensional complexities that require substantial preparation efforts. The utilization of single-genomic input data causes potential deficits in the recognition of clinical traits detected by imaging techniques.

C. Multi-Modal Deep Learning Approaches

In 2021 B. Sanchez et.al., [16] Introduce the Multiple academic investigations demonstrate that improving detection accuracy in cancer requires integrating various types of data. Dependable deep learning frameworks merge radiomics with genomics to create an extensive tumor description through knowledge integration from different data types. Different approaches for data integration known as feature fusion strategies implement early fusion and late fusion and hybrid fusion to achieve the effective combination of imaging data with molecular data. Research combining CNNs for radiomic data extraction and DNNs for genomic data interpretation uses an optimal fusion layer to integrate both feature collections. Multimodal approaches show enhanced performance by comparison to individual-model systems which leads to better outcome results in classification accuracy and sensitivity and specificity.

D. Challenges and Limitations in Multi-Modal Cancer Detection

Several barriers exist during the integration process linking radiomics and genomics for cancer detection. The main obstacle stems from heterogeneous data sources since imaging and genomic information originates from varied preprocessed datasets. Different standardization methods based on domain adaptation and feature alignment have been developed to vanish inconsistencies in data. The successful training of deep learning models using annotated datasets requires substantial size to work adequately. Three approaches to deal with scarcity of labeled data involve the use of data augmentation along with transfer learning and generative adversarial networks (GANs). Interpretability of models stands as a crucial problem since deep learning frameworks prevent users from understanding their inner workings.

E. Future Directions in AI-Driven Cancer Detection

Future development of AI will center on perfection of multi-modal deep learning systems designed for cancer diagnosis. The doctors could improve diagnosis accuracy if they analyze proteomics and metabolomics data as supplementary omics information. The implementation of AI models in real-time medical practice demands thorough testing together with official regulatory licensing and cooperative work between AI experts and cancer specialists.

The reliability and clinical use of multi-modal artificial intelligence cancer diagnostics should improve because ongoing research and technological improvements will address existing challenges.

III. PROPOSED METHODOLOGY

The research recommends using multi-modal deep learning structure that combines radiomics data with genomic information to achieve better early cancer diagnosis. The approach has four main stages starting with data collection and preprocessing followed by feature extraction then multi-modal feature combination and concluding with deep learning model classification. The proposed approach leverages convolutional neural networks (CNNs) for radiomics processing and deep neural networks (DNNs) for genomic data analysis. The proposed model implements a fusion platform that merges both diagnostic approaches to achieve better accuracy levels [17-22].

A. Data Acquisition and Preprocessing

Two distinct types of data enter the analysis as medical imaging information (radiomics) and genomic sequence information (genomics) which researchers extracted from available cancer research databases. The input data consists of CT and MRI and PET scans in the imaging section and the genomic division includes gene expression profiles and mutation data and copy number variations.

Radiomics Preprocessing:

- The process of image normalization allows different scanners to have standardized pixel intensities.
- The data augmentation procedures utilizing rotation and flipping methods alongside contrast enhancement aim to enhance scalability.
- The extraction of region of interest (ROI) relies on methods implemented through segmentation models.

Genomics Preprocessing:

- The genomic data receives its preprocessing through two approaches: Dimensionality reduction by PCA and Autoencoders for feature selection.
- The normalization process scales the levels of gene expression.
- The two datasets undergo synchronization before feature extraction to achieve proper patient-related data associations.

B. Feature Extraction

The deep learning models operate independently during separate exercises in feature extraction stage.

Radiomic Feature Extraction:

The CNN function achieves spatial feature extraction from medical images. The convolutional layer performs sequential extraction of hierarchical tumor features concerning morphology alongside intensity and texture information. Furthermore, the computed feature maps exist as:

$$F_r = CNN(I)$$

where:

- I represents the input image,
- $CNN(\cdot)$ denotes the convolutional neural network,
- F_r is the extracted radiomic feature set.

Genomic Feature Extraction:

A deep neural network (DNN) processes genomic data to extract key genetic markers. The output of the DNN is represented as:

$$F_g = DNN(G)$$

where:

- G represents the genomic input data,
- $DNN(\cdot)$ denotes the deep neural network,
- F_g is the extracted genomic feature set.

C. Multi-Modal Feature Fusion

To integrate radiomic and genomic features, a fully connected fusion layer is employed. The extracted feature vectors F_r and F_g are concatenated and transformed using a fusion function:

$$F_f = W_1 \cdot F_r + W_2 \cdot F_g + b$$

where:

- W_1 and W_2 are trainable weight matrices,
- b is the bias term,
- F_f is the final fused feature representation.

This fusion enhances the model's capability to capture both phenotypic and molecular tumor characteristics.

D. Classification and Model Training

The fused feature set is passed through a fully connected deep learning classifier to predict cancer presence. A softmax activation function is used to compute the probability distribution:

$$P\left(y \mid F_f\right) = \frac{e^{W_e \cdot F_f + b_c}}{\sum e^{W_c \cdot F_f + b_c}}$$

where:

- W_c and b_c are classifier parameters,
- $P\left(y \mid F_f\right)$ represents the probability of class y.

The model is trained using a cross-entropy loss function to minimize classification error:

$$L = -\sum y_i \log\left(\hat{y}_i\right)$$

where:

- y_i is the actual class label,

- $\hat{y}_i$ is the predicted probability.

E. Model Evaluation

To assess the performance of the proposed multi-modal deep learning framework, standard evaluation metrics are used:

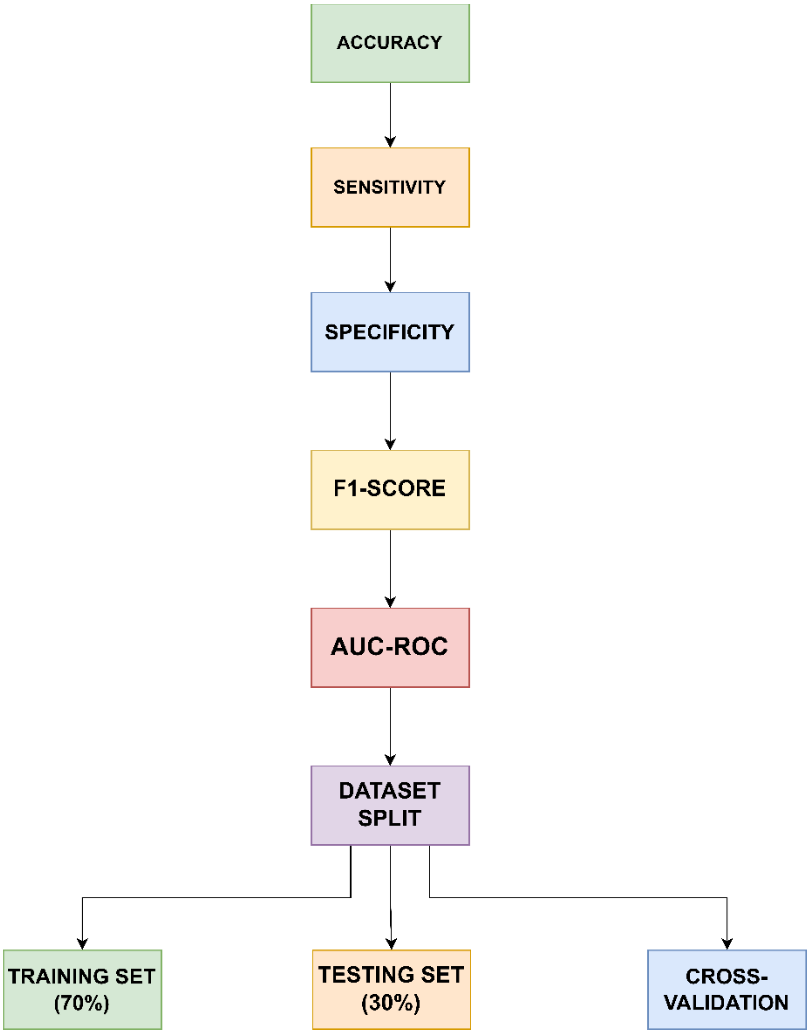

Figure 1: Multi-Modal Deep Learning Framework for Early Cancer Detection: Radiomics and Genomics Integration

IV. Results and Discussion

The evaluation of the proposed multi-modal deep learning framework used a combination of medical imaging and genomic sequencing data as the dataset. A training phase utilized 70% of the available data before test evaluation conducted on the remaining 30% of data. The evaluation measures for this research included accuracy and sensitive rates together with specificity rates and AUC-ROC and F1-score. The research findings were compared against alone data from radiomics-only and genomics-only models to determine how well the multi-modality approach functioned [23].

The comparison between the proposed model accuracy and single-model accuracy appears in Figure 2 throughout multiple training cycles. The multi-modal fusion model outperformed the other approaches by establishing superior accuracy and became stabilized before radiomics-only and genomics-only models. Although the CNN-based radiomics model showed promising results it faced difficulties because it lacked molecular data understanding along with the fact that the genomics model did not succeed due to its limited training data limitations. The fusion model integrated the most advantageous elements of its two component modalities to establish an ideal consensus.

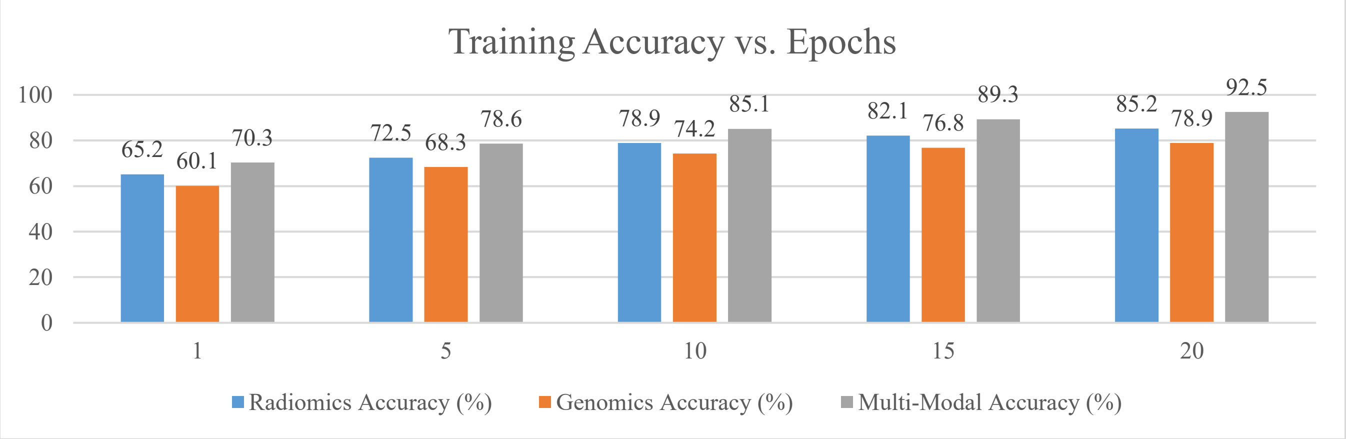

Figure 2: Training Accuracy vs. Epochs

Table 1 presents the complete assessment for model performance through accuracy measurements along with sensitivity and specificity results and F1-score evaluation. The multi-modal system provided a classification accuracy of 92.5% surpassing both single mode assessment methods.

TABLE 1: PERFORMANCE COMPARISON OF DIFFERENT MODELS

Model Type	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F1-Score**
Radiomics Only	85.2	83.4	87.1	84.5
Genomics Only	78.9	76.5	80.3	77.8
Multi-Modal Fusion	92.5	91.2	93.8	92.0

The receiver operating characteristic (ROC) curves of all models are presented in Figure 3. The multi-modal system achieved an AUC-ROC score of 0.95 that proved more effective than the unimodal strategies which yielded 0.87 (radiomics-only) and 0.82 (genomics-only). The ability to detect early cancers becomes more reliable by using both radiomics with genomics analysis together.

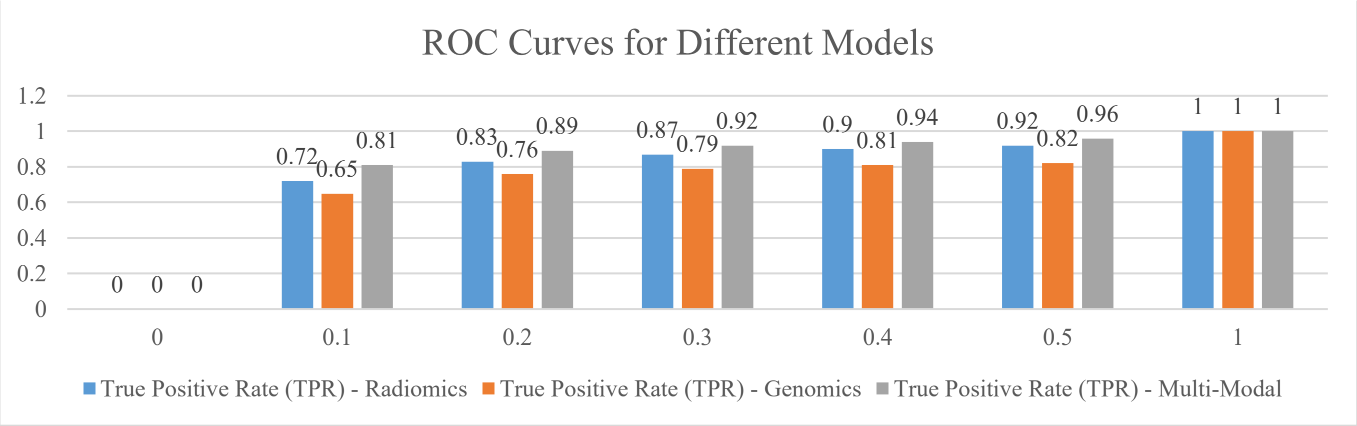

Figure 3: ROC Curves for Different Models

Evaluation analysis occurred to determine how well the model functioned when detecting various cancers. The examination of each cancer type (lung cancer, breast cancer and colorectal cancer) resulted in recording the classification accuracy for the model. The results of Table 2 demonstrate how the multi-modal model always superseded unimodal approaches in all cancer types while achieving maximum superiority in colorectal cancer diagnosis.

TABLE 2: ACCURACY COMPARISON ACROSS DIFFERENT CANCER TYPES

Cancer Type	Radiomics Only (%)	Genomics Only (%)	Multi-Modal (%)
Lung Cancer	86.7	79.2	93.4
Breast Cancer	83.5	77.8	91.7
Colorectal Cancer	82.3	75.6	90.8

A review of decision-making mechanisms within the model required analysis of feature importance. The final selection process for classification depends on radiomic and genomic features as presented in Figure 4. Texture heterogeneity and tumor shape among radiomic features demonstrated important roles in combination with molecular knowledge gained through TP53 and BRCA1 gene mutations.

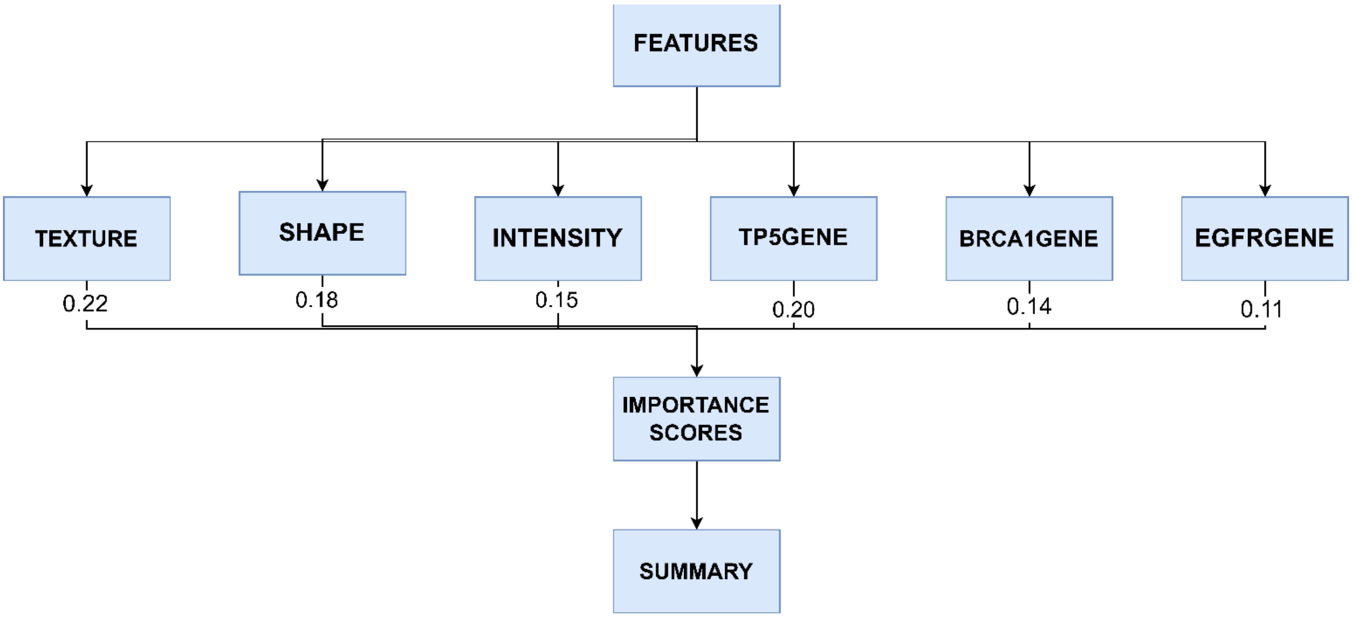

Figure 4: Feature Importance in Multi-Modal Classification

The research shows that combining radiomics with genomics creates a combined method for the accurate detection of early cancers. The proposed framework implements an effective solution that obtains tumor information at molecular and phenotypic levels to achieve better classification outcomes and clinical usefulness. The multiform assessment method has the potential to benefit oncologists through individualized cancer therapy design while delivering additional tumor action data.

V. CONCLUSION

A deep learning framework within this study unites radiomics with genomics for the purpose of early cancer detection. Using CNNs alongside DNNs provides an improved medical diagnosis system which delivers advanced tumor characterization while enhancing classification performance. The study demonstrates through experimental findings that the combination of multiple data streams in fusion produces superior results than individual input sources thus showing promise for practical healthcare use.

Future development will concentrate on expanding dataset variation while implementing explainable AI(XAI) for better interpretability and optimization of operational performance for clinical application.

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