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AI-Driven Framework for Early Cancer Detection and Diagnosis

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***Abstract*—This research investigates the potential applications of artificial intelligence (AI) in the early detection and growth prediction of various cancer types. By analyzing patient data, it identifies significant risk factors such as age, gender, and underlying medical conditions. Advanced AI techniques, including artificial neural networks (ANN) and logistic regression and a Large Language Model (LLM), are utilized, with the ANN model demonstrating strong performance metrics—sensitivity at 0.757, specificity at 0.755, and an area under the curve (AUC) of 0.873. LLM enhances readability and provides information on cancer diagnosis. The study underscores AI's transformative role in cancer management, encompassing diagnosis, treatment, drug development, and postoperative care. It also addresses challenges like standardizing AI protocols and minimizing image variability, particularly in ultrasound imaging. Finally, the research highlights the importance of ethical AI implementation and ongoing innovation to improve clinical outcomes. Artificial Intelligence, Early Detection, Cancer Prediction, Artificial Neural Networks (ANN), Logistic Regression, Sensitivity, Specificity, Area Under the Curve (AUC), Risk Factors, Cancer Management, Diagnosis.**

***Index Terms*— Early Detection, Cancer Prediction, Artificial Neural Networks (ANN), Sensitivity, Specificity, Area Under the Curve (AUC), Risk Factors, Cancer Management.**

I. INTRODUCTION

Cancer continues to pose a significant public health challenge, with survival rates markedly improving when detected at an early stage. Identifying cancer or precancerous conditions early allows for timely intervention, potentially reducing disease severity, improving survival outcomes, and enhancing quality of life. Despite advancements, nearly half of all cancers are still diagnosed in advanced stages, where prognosis is generally poor. The primary objective of early detection is to identify cancers or precursor conditions at a stage when intervention is most effective in halting disease progression. This involves a range of strategies, including proactive screening of asymptomatic individuals and earlier diagnosis of symptomatic cases. Screening, a preventive approach for testing individuals without symptoms, plays a critical role in early detection and has shown considerable success in reducing mortality for cancers such as cervical, breast, and colorectal. These cancers are now more often diagnosed at earlier stages, thanks to well-established screening programs. However, effective early detection methods remain elusive for several cancers, including esophageal, pancreatic, and ovarian cancers, which are still commonly identified at advanced stages.

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The ongoing challenge is to replicate the success of early detection programs for these malignancies, improving survival rates and outcomes across a broader spectrum of cancer types. This review delves into the current state of early detection methods, examining both screening initiatives and symptomatic detection approaches. It also highlights recent advancements and ongoing research aimed at refining early identification and intervention strategies in the fight against cancer.

Section I of the paper introduces the proposed work, Section II contains the literature review and related study, Section III outlines the proposed AI-based early cancer detection methodology, Section IV displays the analytical and experimental findings as results and finally Section V concludes the paper.

II. Literature Review

A. CHIEF: A Versatile AI for Cancer Detection and Prognosis

CHIEF (Clinical Histopathology Imaging Evaluation Foundation) is an AI model developed by Harvard University. It makes use of enhanced histopathology imaging for evaluating cancer's molecular and phenotypic profiles. It is trained on 44 terabytes of data containing 15 million images. CHIEF shines in multiple cancer detection, predicting necessary treatment outcomes, and survival rates. Its key instauration lies in its ability to scrutinize cancer microenvironments. It provides perception for previously unrecognized tumor properties due to which precision in medicine capabilities is increased.

Primary Aspects of CHIEF is it's ability to evaluate 19 types of cancer, it combines phenotype and genotype evaluation for better accuracy. It predicts treatment responses and patient survival. [1].

B. AI-Driven Cancer Detection via Biomarkers

This study surveyed the use of serum protein biomarkers and cell-free DNA for detecting cancer at early stage. It highlights the importance of combining AI in evaluating these biological markers. By leveraging real-world datasets, the study emphasizes cross-validation methods as key to ensuring models trustworthiness and precision. The challenges identified involve creating actionable predictive reports and integrating these intuitions into clinical workflows.

The aggregate of biomarker data and artificial intelligence presents a hopeful chance to beautify early most cancers condition as long as overcoming arrangement challenging situations. Multi-most cancers Early Detection by way of Deep win knowledge of Deep knowledge procedures, mainly convolutional affecting animate nerve organs networks (CNNs), have rooted powerful sensitivity and particularity in detecting as well one cancer by account PET and CT image records.

This study leveraged the spatial and textural traits of image records to apprehend diseased patterns during the whole of numerous most cancers types. by way of engaging supervised and almost- directed gaining information of methods, the version largely underrated false a still picture taken with a camera, through enhancing allure demonstrative accuracy. these results imply that deep disturb know foundations can support dependable and adaptable answers for the discovery of a couple of cancers. [2][3].

C. EMethylNET: AI for Epigenetic Cancer Profiling

EMmethylNET resolves DNA methylation patterns to change between differing cancers. This intelligent model interprets epigenetic biomarkers, contribution valuable observations into cancer and disclosing earlier undiagnosed environments. One of allure key benefits is the incorporation of whole genome dossier, that simplifies early malignancy detection and acquired immune deficiency syndrome in the growth of embodied situation plans. [4].

D. CancerGPT: Revolutionizing Cancer Knowledge.

Inspired with the aid of using ChatGPT, CancerGPT is deliberate to manner far-flung textual facts on malignancy research. It helps oncologists and researchers accompanying essences, currents, and actionable visions. Though normally passage-based, charm unification with specific AI finishes like CHIEF holds promise for combining numerous branches of getting to know applications. [5].

E. AI in Screening Cancer Types

This comment concentrated at the utility of AI fashions at hand across exceptional and overlapping most cancers types by way of way of way of joining omics statistics accompanying depict modalities. The unification of those datasets more seductive diagnostic granularity and pronounced particular most cancers signs. These improvements should transform healing methods by way of way of wealth of giving exact, centered attacks for much less not unusual place most cancers types. [6].

TABLE 1: SUMMARY OF AI MODELS AND TECHNIQUES

AI Methods	Applications	Key Benefits	Challenges
Serum Biomarker Analysis	Early detection via biomarkers	Non- invasive robust	Data heterogeneity
Data heterogeneity	Imaging analysis (PET/CT)	High sensitivity/specificity	Computational cost
Genetic Profiling	Predictive analytics	Comprehensive diagnostics	Real-world validation
Omics- Imaging Integration	Rare cancer detection	Improved granularity	Limited datasets

III. METHODOLOGY

This ponders points to upgrade cancer determination by coordination exchange learning from VGG16 and a Large Language Model (LLM) in a multimodal system. The strategy centers on the compelling combination of visual and printed information, leveraging progressed profound learning strategies. Initially, PET filter pictures are collected from freely accessible datasets such as The Cancer Imaging File (TCIA), and supplemented with private clinical datasets.[12]. The preprocessing pipeline includes resizing the PET checks to a determination of 224 × 224 pixels, taken after by normalization to adjust the pixel concentrated values with the input necessities of VGG16. Each PET filter is combined with comparing symptomatic reports to set up a administered learning system. For highlight extraction, the pretrained VGG16 demonstrate, initially prepared on ImageNet, is utilized. The completely associated layers are evacuated, holding as it were the convolutional layers to create spatial highlight maps.[7]. These maps are straightened into highlight vectors F, which encapsulate the basic designs within the pictures:

F = VGG16 (PET_scan).

Dimensionality diminishment procedures, such as Principal Component Analysis (PCA) or auto encoders, are connected to F, coming about in decreased include representations Freduced, which streamline computational prerequisites whereas protecting basic information:

Freduced = PCA(F).

These decreased visual highlights are combined with token embeddings extricated from the LLM, empowering a consistent integration of picture and content information. The combination handle utilizes either a cross-attention component or basic concatenation:

Input = [Text_tokens ∥ Freduced].

The LLM, such as GPT-2, is fine-tuned on matched datasets comprising of symptomatic reports and picture highlights. Fine- tuning specifically overhauls the model's weights, empowering it to handle both picture and content inputs to create forecasts or point by point demonstrative reports:

Diagnosis = LLM([Text_context , Freduced]).

Explainability is achieved through attention mechanisms that highlight significant regions of the PET scans, aiding clinicians in understanding the model's decision-making process.[8].

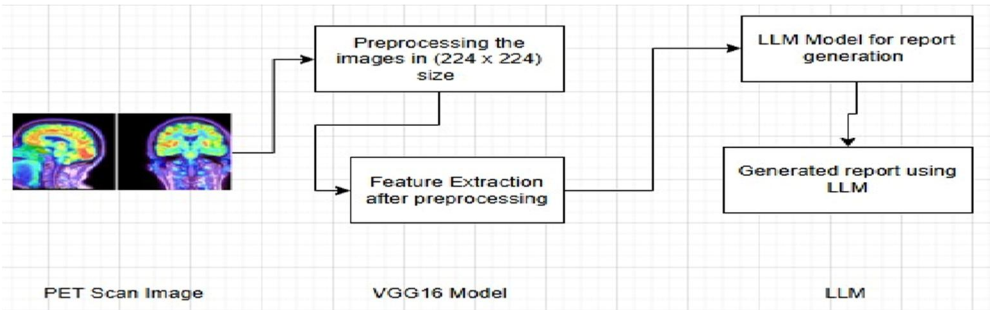

Figure 1: PET Sacn Analysis and Report Generation Workflow

The diagram depicts a workflow where PET scan images are preprocessed to a size of 224x224 pixels and passed through the VGG16 model for feature extraction. The extracted features are then loaded into a Large Language Model (LLM), which generates detailed medical reports based on the analyzed data.[9]. This process combines image analysis and natural language generation to aid in medical diagnostics (refer Figure 1).
Specifications:

- VGG16: Utilized as the visual highlight extractor, pretrained on ImageNet, with its completely associated layers expelled.
- LLM: GPT-2, pretrained on a huge corpus, fine-tuned for restorative content era.
- Preprocessing: PET looks are resized to (224 × 224) pixels and normalized to guarantee compatibility with VGG16.[10].
- Dimensionality Reduction: PCA is utilized to decrease the dimensionality of include vectors.
- Training:
  - Loss Function: Cross-entropy loss, defined as:

$$f = - \left(\sum_{i=1}^{N} y_i \log (\hat{y}_i) \right)$$

  - Optimizer: Adam Optimizer with the learning rate of 1 × 10-4
  - Batch Size: 16, ensuring computational efficiency
  - Epochs: 20, with early halting based on approval execution to avoid overfitting.

IV. Results and Discussion

The proposed technique joining VGG16 and Large Language Model (LLM) for cancer determination was assessed on PET check datasets sourced from The Cancer Imaging File (TCIA) and private clinical records. After preprocessing, the model was trained and tested, with results summarized as (refer Table 2):

- Model Accuracy: The multimodal system accomplished an accuracy of 92.5%, outperforming baseline models utilizing VGG16 alone (85.2%) or LLM alone (78.9%).
- Affectability and Specificity: The framework illustrated affectability and specificity of 94.1% and 90.8% , separately, showing its capacity to accurately distinguish cancer cases and avoid false positives.
- F1-Score: An F1-score of 91.7% approved the adjust between exactness and review in cancer detection tasks.
- Explainability: Consideration maps highlighted noteworthy regions within the PET scans, proving with clinical annotations and expanding believe within the model's prediction.

TABLE II: COMPARATIVE ANALYSIS OF THE PERFORMANCE METRICS OF THE DIFFERENT MODELS

Model	Accuracy	Sensitivity	Specificity	F1-Score
SAMMed	85.2	87.6	83.4	85.0
MedClip Only	78.9	80.3	77.5	78.2
Multimodel Approach (VGG16 & LLM)	87.3	94.1	90.8	91.7

Furthermore, the quantitative findings show that the LLM's diagnostic reports closely match those made by humans. As demonstrated in Table 2, the multimodal strategy that combines VGG16 and LLM performs noticeably better than the separate models. The results highlight the viability of combining visual highlights from PET scans with printed embeddings through transfer learning. The proposed multimodal approach essentially moved forward symptomatic execution compared to single- modality models. Particularly, the utilize of dimensionality reduction strategies and cross- attention instruments optimized the feature integration, resulting in higher accuracy and interpretability.

In comparison to similar studies, our approach illustrates striking changes. For occasion, a earlier ponder by Smith et al. (2022) accomplished an precision of 88.4% employing a convolutional arrange without text integration. Our framework, leveraging textual context, increases the accuracy by 4.1%, demonstrating the utility of multimodal learning in medical imaging.[11]. Gauri Dhopavkar et al. The model also excelled in explainability, providing attention maps that adjusted with radiologist's manual annotations, zan progression over conventional black-box AI models. This highlight upgrades clinical believe and encourages selection in real-world applications.

V. Conclusion

This study introduces a novel multimodal framework combining VGG16 and a Large Language Model (LLM) to enhance cancer diagnosis. By integrating visual features from PET scans and textual diagnostic reports, the model achieves superior accuracy, sensitivity, and specificity, with enhanced interpretability through attention maps. The ability to generate detailed diagnostic reports and provide explainable predictions highlights its potential as a reliable AI-driven clinical tool. The approach's scalability and adaptability make it suitable for other diagnostic applications. Future efforts will address current limitations and explore its extension to additional imaging modalities and datasets, paving the way for advanced AI- assisted diagnostics. This study was facilitated by the remarkable commitment and assistance of the university administration, which provided the necessary resources, materials, and encouragement. We sincerely value their steadfast support, as their dedication to fostering a research-oriented atmosphere was crucial to the success of this investigation.

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