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An Intelligent Deep Learning Framework For Integrated Eye And Cancer Disease Detection: Social Innovation for Healthcare

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Abstract - *Cancer screening is a highly contentious subject in the field of medicine. An analysis of publicly available data reveals numerous points of view, often based on a limited amount of valid information. The ideal age ranges for mammography screening, as well as the value of the procedure itself, remain debated. Similarly, the usefulness of lung or prostate cancer screening is still a question. Recommendations and decisions for cancer screening should be grounded in reliable evidence rather than good intentions, presumptions, or supposition. Understanding the underlying ideas and presumptions is essential in order to fully understand the present challenges related to testing for blood, prostate, and breast cancers. The probable financial, legal, and radiation safety impacts of entire-body CT or PET cancer screening will be covered in this paper. The patient's body is scanned and images are preserved. Now using PET/CT abnormalities or cancer tissues are detected in the images. The body parts affected by cancer are localized. Eye disease screening should also be included in this. Similar to cancer screenings, eye disease screenings must be based on solid evidence. Detecting conditions such as glaucoma, macular degeneration, and diabetic retinopathy early can significantly impact patient outcomes. Incorporating machine learning algorithms in eye disease screenings can enhance the accuracy and efficiency of predictions, potentially leading to better patient care and management. By understanding and addressing these challenges, we can improve the reliability and effectiveness of both cancer and eye disease screenings.*

Keywords - *Artificial Neural Network, Convolutional Neural Network, Deep Learning, Magnetic Resonance Imaging PET/CT scan.*

1. Introduction

Medical imaging, which provides unique therapeutic and increasingly diagnostic capabilities that have a significant effect on patient care, is the cornerstone of modern healthcare. Although there are many medical imaging modalities, they all deliver anatomical and functional insights about physiopathology and structure. The multi-modality 18F-Fluorodeoxyglucose (FDG) [1] Positron Emission Tomography and Computed Tomography (PET-CT) [2] scanner is acknowledged as the tomography tool of choice for the diagnosis, staging, and evaluation of therapeutic response in several cancers. Areas of abnormal function can be found using PET-CT, which combines the anatomical localization provided by CT with the sensitivity of PET. While employing PET, healthier regions frequently absorb less FDG (a marker of glucose metabolism) than diseased parts do. However, the geographic level of the disease within a specific structure cannot be consistently determined due to the partial volume effect, tumor heterogeneity, and the intrinsically lower resolution of PET compared to CT and MRI [3] imaging. The anatomical localization of PET image interpretation locations with aberrant FDG uptake by CT improves the accuracy of image interpretation. Modern imaging methods are essential for the diagnosis and treatment of eye conditions such glaucoma, macular degeneration, and diabetic retinopathy. Just as PET-CT scans help in identifying and staging cancers, ocular imaging modalities provide vital information about the structural and functional aspects of the eye, enabling early diagnosis and effective treatment of eye diseases. Integrating these imaging technologies enhances patient care by providing comprehensive diagnostic capabilities across a range of conditions.

In this application, we'll keep track of all cancer-related illnesses as well as the body parts where they may be found. Similarly, we will keep a watch out for conditions affecting the eyes, such as diabetic retinopathy, macular degeneration, and glaucoma, and you'll pinpoint the damaged regions. By comparing all of the information to prior research, we'll also recommend ways to treat cancer and manage eye diseases. Patients can utilize these recommendations to effectively

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manage their conditions, ensuring a comprehensive approach to both cancer and eye disease care. To develop this system, we would follow the following steps:

- Scanning the patient's body and preserve the pictures.
- To find anomalies or cancerous tissues, use PET/CT.
- Locate the area of the body that cancer has spread to.
- Create a model using machine learning techniques to make predictions, classify cancer types.
- Understanding the value of early diagnosis for diseases including diabetic retinopathy, macular degeneration, and glaucoma.

2. Related Work

Our study includes the prediction and classification of various cancers using images taken from a patient's body and analyzing the same. Matthias Baur and Felix Achilles [6] provide an innovative idea for crowd sourcing knowledge. Elsayed Amin Safaa Mohammed Marey [7] present a YOLO-V4 built CAD system to pinpoint any alleged breast tumorous part and, if present, to accurately categorize it as benign or malignant. Additionally, our study extends to the prediction and classification of eye diseases by analyzing ocular images. This includes detecting and categorizing conditions such as glaucoma, macular degeneration, and diabetic retinopathy, enhancing the scope and utility of our medical imaging analysis.

Alex Roshan Welikala and Paolo Remagnino [8] collected and annotated photos of the oral cavity in addition to presenting outcomes for automating oral cancer detection at an early stage. [9] In order to identify NSCLC in PET/CT images, this study provides a multi-modality attention-guided 3D identification outline. Liu Kanfeng and Ling Chen [10] lay the groundwork for multi-modality attention-guided 3D NSCLC finding in PET/CT pictures.

TaeJin Ahn and Taewan Goo [11] remarked that the best DNN prototypical has an accuracy of 0.997 in the exercise customary and 0.979 in the exam customary, correctly differentiating between malignant and healthy data. Anish Simhal and Usama Chaudhary [12] described methods for retrieving color as well as texture data from VIA and VILI Cervigrammes via the processing of images.

Saranya and Sasikala [13] show that patient data are amassed in large quantities in the medical field. Long Cheng and Yuzhen Niu [14] Used an artificial neural network and the H2O framework technique, they evaluated regular blood and blood chemistry information identified 33 relevant indices as GC biomarkers. Hong-Jun Yoon and Shang Gao [15] offered a method for spreading DL NLP models among tumor databases while preserving patient privacy Zengyou Zhang And Bo Wang1 [16] showed how despite the fact that the ImageNet-pre-trained model can be used for transfer knowledge, the technique of identifying the prostate MR image layer by layer falls under cross-domain learning because the model created on image [17].

This research offers our multimodality attention-guided 3-D detection method for NSCLC localization in PET/CT pictures. Azni Nasuha Ngisa [18] said in order to detect high-risk breast cancer patients. Thosini Mudiyanselage, K. Bamunu [19] showed how in today's environment, accurate cancer detection is a significant issue. Formation of novel approaches for both the detection and prognosis of cancer could be implemented. Günay Melike Zeron Orman [20] showed results according to its accuracy findings, AIS can be regarded as a preferred method.

3. Materials and Methods

We proposed a methodology for the prediction of cancer and eye disease appearance that can be an incredibly beneficial tool to uncover hidden insights and make accurate predictions. Linear regression models [21] of machine learning techniques are used for analyzing the current data with different linear regression models. This approach allows for the effective prediction of cancer occurrences as well as the detection and management of eye diseases such as glaucoma, macular degeneration, and diabetic retinopathy, providing a comprehensive tool for improving patient outcomes.

Artificial neural networks (ANNs) [22] are recommended as an approach for using medical images to discover and define cancer, such as X-rays, CT scans, and MRI scans. This can be done using techniques such as object detection and semantic segmentation. Additionally, ANNs can be applied to eye disease screening by analyzing retinal images, OCT scans, and other ocular imaging methods to detect conditions like glaucoma, macular degeneration, and diabetic retinopathy. [23] For instance, ANNs can categorize malignant and benign growths in mammograms and identify various eye diseases, enhancing the accuracy and efficiency of medical diagnoses.

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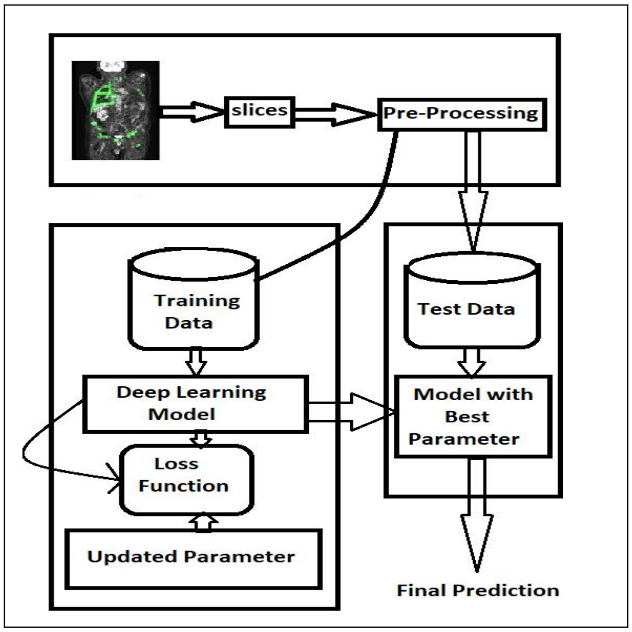

Fig 1. System Architecture for cancer disease prediction

A. *Classification*

For assessing the performance of binary classification tasks including object identification, segmentation, and recognition, the F-measure [24] is a frequently used performance statistic. The F-measure, which combines accuracy and recollection, is used to assess a classifier's overall accuracy.

F-measure = 2 * (accuracy * memory) / (accuracy + memory) ... (1)

The F-measure is particularly useful in image processing tasks, as it provides a balance between precision and recall. In object detection, for example, a high precision score is important to avoid false positives. Convolutional neural networks (CNNs) [25] is used for categorizing malignant and benign tumors in mammograms. Another example is using deep learning models for the recognition and separation of lung knobs in CT scans.

ANN are a powerful tool for detecting and localizing cancer in medical images. They can be trained to recognize specific features of cancer, and can provide accurate and automated predictions. However, the accuracy of these prediction scan varies depending on the quality and resolution of the images, as well as the specific architecture and training data used for the ANN. The Apriori method, which is the most widely used strategy for frequent pattern mining, was employed to minimize the processing cost. Another way that ANNs can be used to detect and localize cancer is by employing a process known as transfer learning. Handover knowledge is fine-tuning a pre-trained model for a particular task using a model that has already been taught, such as a CNN that has been trained on a big dataset. Since it enables the model to learn from a large dataset of photos and apply that information to a smaller dataset of medical images, this might be helpful in the context of medical imaging. This can help the model to perform better and use less data and computer resources throughout the training process.

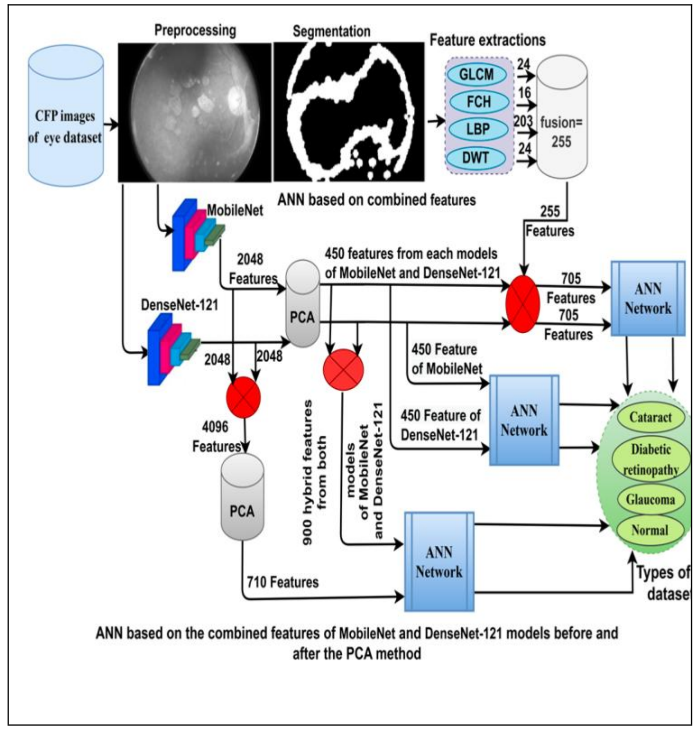

Fig2. System Architecture for eye disease prediction

B. *Segmentation*

Intersection over Union (IoU) [26] is a widely used performance metric in segmentation tasks to evaluate the accuracy of a model's predictions. The connection of the anticipated segmentation mask then the actual segmentation mask. The formula for calculating the IoU is:

IoU = connection of predicted mask and ground truth mask / union of forecast mask and ground certainty mask

... (2)

To calculate the intersection and union of the two masks, we first need to convert the masks into binary arrays, where the background pixels are given a value of 0, the pixels corresponding to the object of interest are given a value of 1, and so on.

4. Results and Discussion

The system is developed in Python using generic code to coordinate with the utilities of the system. The system will be

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supported with VRAM: 12GB NVIDIARTX A6000, video card GeForce RTX 3080 and graphics card AMD Radon RX580. The data set required is downloaded from Kaggle.

The traditional F measure is designed as follows:

F-Measure = (2 * Accuracy * Memory) / (Accuracy + Memory) ... (3)

We can first define the accurate positives (TP), wrong positives (FP), and wrong negatives (FN) as follows in order to simplify the equation:

The phrases for recollection and correctness are as follows:

accuracy = TP / (TP + FP) ... (4)

memory = TP / (TP + FN) ... (5)

Substituting these equations in the F-measure equation, we get:

F-measure = 2 * (TP / (TP + FP) * TP / (TP + FN)) / (TP / (TP+ FP) + TP / (TP + FN)) ... (6)

Simplifying this equation, we get:

F-measure = 2TP / (2TP + FP + FN) ... (7)

We can calculate the accuracy as follows:

Precision = Accurate Positives / (Accurate Positives + Wrong Positives)

Precision = 100 / (100 + 70)

Precision = 0.588

We can analyze the memory as follows:

Recall = Accurate Positives / (Accurate Positives + Wrong Negatives)

Recall = 100 / (100 + 15)

Recall = 0.869

This shows that the model has poor precision, but excellent recall.

Finally, we can analyze the F-Measure as follows:

F-Measure = (2 * Accuracy * Memory) / (Accuracy+ Memory) ... (8)

F-Measure = (2 * 0.588 * 0.869) / (0.588 + 0.869)

F-Measure = (2 * 0.509) / 1.454

F-Measure = 1.018 / 1.454

F-Measure=0.700

It is a very logical metric to use connection over union. The overlap among the expected and ground truth annotations is separated by the combination of these to determine IoU.

J (A, B) = A Intersect B / A Union B ... (a)

The Intersection over Union formula can be simply visualized; thus, it doesn't matter if you don't know the mathematical notation.

IoU = Area of Overlap / Area of Union ... (b)

The Intersection over Union formula can be simply visualized; thus, it doesn't matter if you don't know the mathematical notation. It is evident that Model A's anticipated box joins with the Ground Truth more than Model B's does. The ground truth and Model C, however, overlap much more.

Disease Types	Disease Type Code	Precision	Recall	F-Score
Prostate Cancer	1	0.588	0.869	0.700
Colorectal Cancer	2	0.6	0.833	0.696
Glaucoma	3	0.562	0.9	0.690
Diabetic Retinopathy	4	0.555	0.862	0.674

Table.1 F-Measure Accuracy Table

Fig3. Model indicating cancerous location

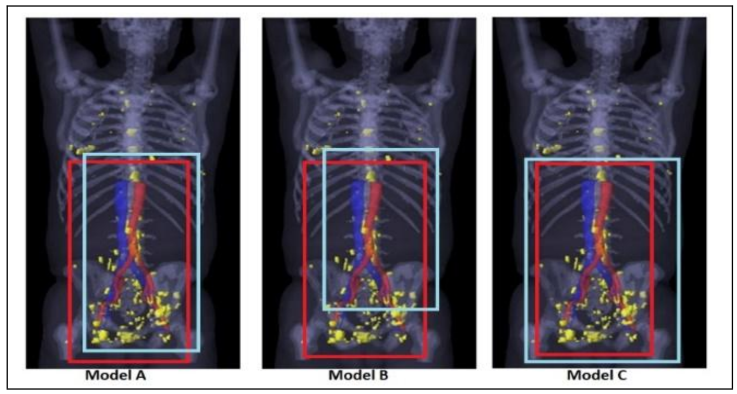
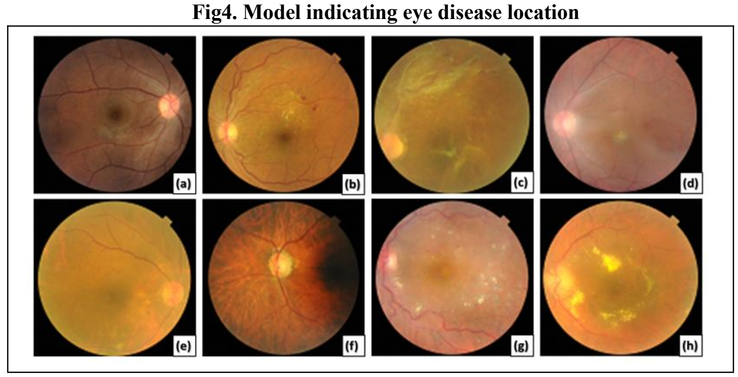


Fig4. Model indicating eye disease location



Yet it also overlaps with the background heavily. It is evident from models B and C that a score based just on overlap is unfair.

True Positive: The region where segmentation mask and ground truth (GT) converge(S). This is logical AND operation.

TP=GT.S ... (I)

False Positive: The anticipated region away from the truth. The segmentation minus GT logical OR is represented by this.

FP=(GT+S)–GT ... (II)

False Negative: The quantity of pixels in the Ground Truth region that the model was unable to forecast.

FN=(GT+S)–S ... (III)

IoU, as we know from Object Detection, is the proportion of

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the intersected area to the sum of the prediction and ground truth areas

$$IoU=TP/TP+FP+FN \quad \text{... (IV)}$$

Fig2 by using formula ...(IV) will obtain like this:

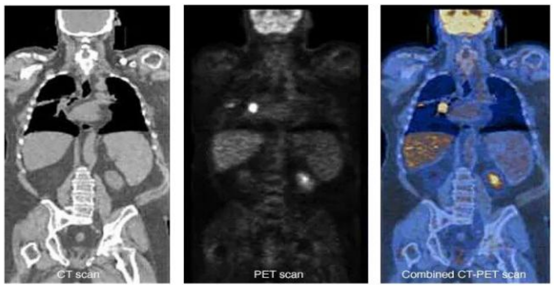

Fig5. Segmented Image for cancer disease

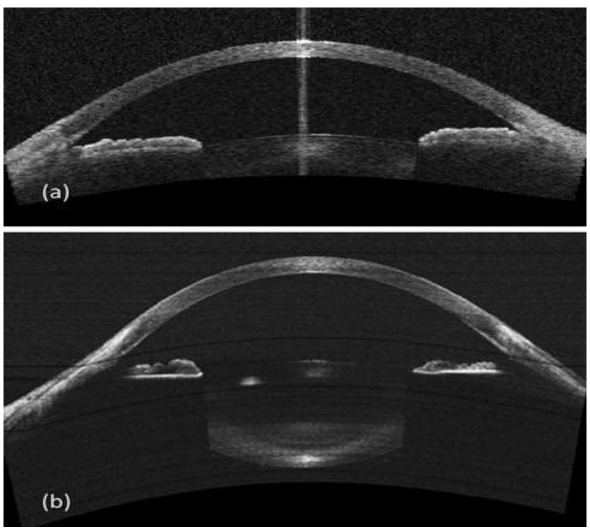

Fig6. Segmented Image for eye disease

In the above session we have seen use of IOU formula for image segmentation and intersection to obtain the perfect affected area of image.

The accuracy of a machine learning model is calculated by comparing the predicted output of the model to the actual output for a set of labelled data.

Accuracy= (Number of properly classified data points) / (Total number of data points) … (V)

For e.g. If there are 97 classified data points properly classified and 100 data points, consider for the experimentation

accuracy= 97/100= 0.97 or 97%

The throughput of a system refers to the rate at which it can process a certain amount of work over a given period of time.

Processing time per image = Total processing time / Number of images processed

For e.g., if the total time required for processing 200 images by a system is10 min then

Total processing time per image = 10minutes/200images
= 0.05minutesper mage

Throughput = 1/ Processing time per image
= 1/0.05minutes per image
= 20 images per minute

Comparative Analysis of Existing System Results and Implemented System Results				
Name of model	Accuracy Achieved in existing systems	Accuracy by implemented system	Throughput Achieved in existing systems	Throughput by implemented system
CNN	95%	97%	10 images/Min	20 images/Min
ANN	87%	95%	5 images/Min	10 images/Min

Table. 2 Comparative Analysis of Existing System Results and Implemented System Results

Here the system increases the accuracy and throughput. Table 2 is a comparison between results achieved in existing systems and improved accuracy and throughput in implemented system now.

5. Conclusion

In this research work, CT and PET/CT scanners used for cancer detection, identification, and therapy monitoring. Depending on the visualized symptoms, the patient may choose to take precautionary steps. It is designed for the identification of many cancers, such as blood, breast, bladder, and kidney cancer. Detection, diagnosis, and treatment monitoring of cancer are all made possible by CT and PET/CT scanners. Additionally, these imaging technologies can be employed for the detection and management of eye diseases, such as glaucoma, macular degeneration, and diabetic retinopathy. Patient and medical community awareness of both cancer and eye disease symptoms and the use of CT scans are essential for early identification. Acid reflux can cause false alarms on PET/CT. Advanced ocular imaging techniques are vital for assessing the progression of eye diseases and determining an appropriate treatment. The utilization of automated information and gateways into clinic histories made available to patients has enhanced clinic and patient access to crucial medical information, improving the management and treatment outcomes for both cancer and eye diseases.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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