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Pancreatic Cancer Detection Using Deep Learning with Inception V4 and Grey Wolf Optimization

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Abstract— Pancreatic cancer continues to pose significant diagnostic challenges due to its late-stage symptom onset and subtle imaging characteristics. In this Paper, a robust computer-aided detection approach is proposed, integrating deep learning with bio-inspired optimization to improve diagnostic accuracy using CT images. The architecture leverages the Inception V4 network to extract deep semantic features capable of capturing minute variations in pancreatic tissue. To further refine the model's performance, Grey Wolf Optimization (GWO) is employed for tuning critical model parameters and identifying the most relevant features.The Inception V4 model identifies key patterns in the images, while the Grey-Level Co-occurrence Matrix (GLCM) extracts important texture information. GWO is then used to optimize these features for better classification accuracy. The process includes image segmentation and morphological refinement to highlight areas of interest, such as possible tumors. In addition to deep learning features, statistical texture attributes derived from the Gray-Level Co-occurrence Matrix (GLCM) namely Contrast, Energy, and Entropy are computed to characterize fine-grained texture irregularities that often correlate with malignancy. The fusion of deep and handcrafted features enhances classification reliability. Experimental validation confirms that the combined method achieves superior performance. The fusion of Inception V4 and GWO enhances both the sensitivity (detecting cancer when present) and specificity (minimizing false positives), promising a significant improvement in medical image analysis for pancreatic cancer detection.

Keywords— Pancreatic Cancer Detection, Deep Learning, Inception V4, Grey Wolf Optimization (GWO),Grey Level Co-occurrence Matrix (GLCM), CT Imaging.

I. INTRODUTION

Pancreatic cancer ranks among the most fatal types of cancer globally, characterized by a five-year survival rate of less than 10% [1]. The poor prognosis largely results from the disease's silent nature in its initial stages and the pancreas's deep-seated location within the body, which collectively hinder early clinical detection [2]. In most instances, diagnosis occurs only after the malignancy has spread to distant organs, significantly limiting therapeutic effectiveness. Therefore, the ability to detect pancreatic cancer at an early and accurate stage is vital for enhancing patient survival rates.

The integration of artificial intelligence (AI), particularly deep learning, has significantly advanced medical image processing in recent years. Among these approaches, Convolutional Neural Networks (CNNs) have emerged as powerful tools for automatically identifying and classifying patterns in medical imaging, including applications in radiology, pathology, and cancer diagnostics [3]. Unlike conventional machine learning algorithms that depend on manually engineered features, CNNs autonomously learn relevant patterns from input images, leading to improved diagnostic accuracy. Nonetheless, their performance is highly dependent on the selected network design and the fine-tuning of associated hyperparameters.

The Inception V4 model, a refined version of the original GoogLeNet, incorporates both inception structures and residual links to create a deeper network architecture that maintains computational efficiency [4]. This hybrid modular configuration allows the network to perform multi-scale analysis, which is highly beneficial in medical image analysis tasks, especially where tumor regions present significant variability in shape and texture. However, the effective training of such deep neural networks demands meticulous calibration of multiple hyperparameters, including the learning rate, dropout probability, and the size of dense layers, to mitigate overfitting and ensure stable model training.

To simplify and automate this complex tuning process, metaheuristic optimization techniques have become increasingly popular. One such method is the Grey Wolf Optimization (GWO) algorithm, which stands out for its ease of implementation, rapid convergence characteristics, and robust balance between global exploration and local exploitation [5]. GWO is modeled after the social dominance and coordinated hunting strategy of grey wolves, enabling it to adaptively search for near-optimal hyperparameter settings in high-dimensional problem spaces.

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This research introduces a novel hybrid deep learning approach for pancreatic cancer identification by integrating the Inception V4 convolutional network with the Grey Wolf Optimization (GWO) algorithm. The Inception V4 model is utilized to extract high-level discriminative features from medical imaging data, while GWO is employed to fine-tune essential hyperparameters, thereby boosting the model's predictive capability. The proposed method is rigorously evaluated using a publicly available dataset comprising labeled CT scans. Comparative analysis with standard CNN-based classifiers and alternative optimization algorithms demonstrates superior results in terms of diagnostic accuracy, sensitivity, and specificity. These findings suggest that the developed framework has strong potential for use in clinical diagnostic tools aimed at early detection of pancreatic malignancies.

II. Related Work

The use of artificial intelligence, especially deep learning, has significantly impacted the field of medical image analysis. Recently, numerous models have been developed to aid in the early detection of pancreatic cancer using computed tomography (CT) images. These images are favored for their exceptional spatial resolution and capability to depict soft tissue details. Despite these advancements, achieving precise and timely diagnoses remains a challenge due to the subtle and diverse characteristics of pancreatic lesions.

Numerous prior investigations have assessed the effectiveness of conventional convolutional neural network (CNN) models—such as AlexNet, VGGNet, and ResNet in the classification of pancreatic tumors [6], [7]. While these networks achieved moderate levels of accuracy, their limitations in capturing discriminative features—primarily due to inadequate network depth or the absence of multi-scale feature extraction—have been noted. The introduction of ResNet, which incorporates a residual learning mechanism, mitigated issues like the vanishing gradient in deep architectures and has proven useful in various medical imaging applications, including pancreatic region segmentation and lesion localization [8]. Nonetheless, the high heterogeneity in tumor structure and appearance necessitates the exploration of more robust and sophisticated deep learning frameworks.

In recent years, the Inception architecture series has gained attention for its effectiveness in modeling spatial features at multiple scales by employing varied filter sizes within individual network layers. Among these, Inception V4 introduced by Szegedy and colleagues integrates residual pathways to improve gradient propagation and optimize the training of deep neural networks. This enhanced design has yielded high accuracy in complex visual recognition benchmarks and has been increasingly utilized in medical imaging tasks, including the identification of lung nodules, classification of brain tumors, and segmentation of hepatic lesions.

In pancreatic cancer diagnosis, deep learning frameworks have been widely explored for tasks such as tumor segmentation and classification using imaging techniques like CT and MRI. For instance, Liu et al. [9] introduced an enhanced U-Net architecture to segment the pancreas region effectively. Meanwhile, other researchers have adopted ensemble-based methods to boost model robustness across heterogeneous datasets. Despite these advancements, many existing solutions rely on fixed hyperparameter configurations, which can limit adaptability when dealing with diverse imaging characteristics and patient variability.

To address the challenges associated with manual hyperparameter selection in deep learning models, researchers have increasingly adopted metaheuristic optimization strategies. Various approaches, including Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO), have been employed for this purpose, as evidenced in existing studies [10]. Notably, the Grey Wolf Optimization (GWO) technique has gained attention for its robust balance between global search (exploration) and local refinement (exploitation), alongside its simplicity in practical implementation. GWO has demonstrated promising outcomes in tuning convolutional neural network (CNN) configurations, particularly in domains such as breast cancer detection and dermatological image classification.

Although the effectiveness of deep learning models has been widely established, the application of Grey Wolf Optimization (GWO) in conjunction with advanced architectures such as Inception V4 for detecting pancreatic cancer in CT images has not been extensively studied. This work introduces a novel framework that leverages GWO to fine-tune the Inception V4 network for the automated identification of pancreatic cancer from computed tomography scans. By integrating the comprehensive feature extraction capability of Inception V4 with the dynamic optimization behavior of GWO, the proposed method aims to enhance classification performance and overall model reliability.

III. Proposed Methodology

Inception V4 is a state of the art deep learning architecture designed for image recognition tasks, and it is a further advancement from earlier Inception models. It introduces deeper and wider convolutional layers while maintaining computational efficiency through careful design choices. The architecture uses factorized convolutions, which help to reduce the number of parameters while retaining the ability to detect complex features in images. In the context of medical imaging, Inception V4 excels at extracting intricate patterns, textures, and edges, making it an ideal choice for detecting anomalies such as cancerous cells in CT Images. The Inception-v4 model is an improvement on Comparision to previous Inception models like Inception-v3, this inception V4 is more unified and simplified network structure and more inception modules, inception-v3 inherits many of the previous methods.

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This research introduces an integrated methodology combining deep neural networks and bio-inspired optimization for the detection of pancreatic cancer. The system leverages the Inception V4 deep convolutional network to extract discriminative features and perform classification tasks. Simultaneously, the Grey Wolf Optimization (GWO) algorithm is utilized to automate the tuning of critical hyperparameters, thereby improving the model's predictive accuracy. The entire process is composed of several key phases: preprocessing of medical imaging data, feature learning using Inception V4, hyperparameter refinement through GWO, and final classification. The complete framework is illustrated in Fig. 1.

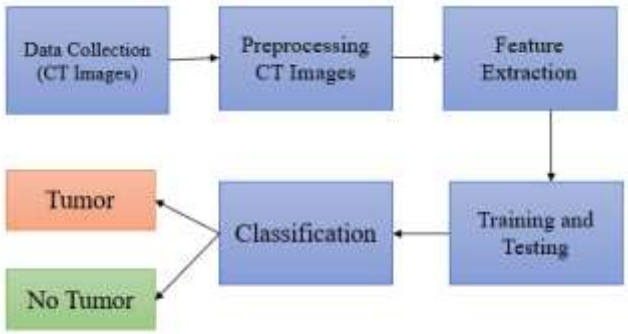
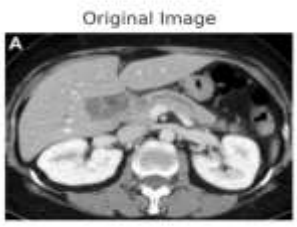


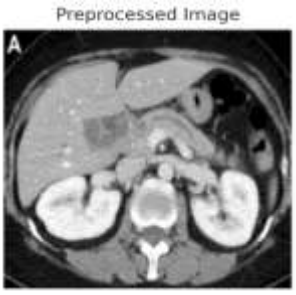
Fig:1. Block Diagram

A) Preprocessing of Pancreatic CT Images:

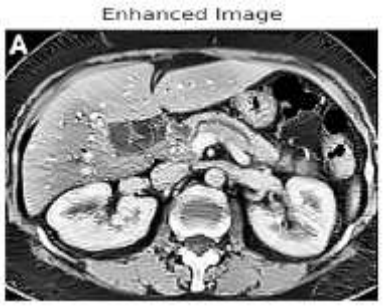
Due to variations in spatial resolution, contrast levels, and anatomical differences in CT scans of the pancreas, preprocessing plays a crucial role in standardizing the data for model compatibility and enhancing recognition performance. All input images are resized to match the expected dimensions of Inception V4 (e.g., 299×299 pixels). Contrast is improved using histogram equalization, and intensity normalization is carried out by scaling pixel values between 0 and 1. Additionally, to increase the volume and diversity of training samples, augmentation operations such as flipping, rotation, resizing, and shifting are applied. The below Images show the example of an Original Image Converted into Enhanced Image using Median Filtering and CLAHE



(a)



(b)



(c)

Fig:2 a. Original Image, b. Preprocessed Image, c. Enhanced Image

B) Deep Feature Learning through Inception V4:

The Inception V4 model integrates Inception modules with residual paths, allowing for stable and efficient training of deep networks. Its architecture enables extraction of both local and global features at multiple scales, which is essential for identifying complex and irregular tumor patterns in pancreatic scans. For this study, the pre-trained Inception V4 is adapted and fine-tuned to the specific dataset. The terminal dense layers are restructured to support either binary or multiclass classification depending on the clinical requirement.

C) Hyperparameter Optimization Using Grey Wolf Optimization:

Optimizing hyperparameters like learning rate, dropout probability, batch size, and dense layer configuration is often a non-trivial task. To automate this step, the Grey Wolf Optimization algorithm is employed, which is inspired by the social hierarchy and cooperative hunting techniques of grey wolves in nature. Each individual in the GWO population represents a unique set of hyperparameters. The optimization goal is defined using a fitness function based on classification accuracy or the value of cross-entropy loss. Through iterative behaviors simulating encircling, tracking, and attacking prey, GWO efficiently explores the hyperparameter space and converges toward an optimal solution. H=(h1,h2,…,hk) be a set of hyperparameters for training Inception V4.

Fitness(H)=Accuracyval (Train (InceptionV4,H))

GWO updates each solution (hyperparameters) using:

$$A=2a \cdot r1- a \ \ and \ \ C=2 \cdot r2$$

D) Model Training and Performance Evaluation:

Identifying the best hyperparameter configuration via GWO, the tailored Inception V4 network is trained on the complete training set. Model effectiveness is gauged using an independent test dataset, with evaluation carried out using several performance indicators including accuracy, recall (sensitivity), specificity. To further assess model reliability and minimize overfitting, cross-validation techniques are applied throughout the training and testing stages. Performance validation plot for pancreatic cancer

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detection using Inception V4 optimized with GWO. The model achieved the lowest validation error (MSE = 0.017288) at epoch 10, indicating optimal generalization before overfitting begins.

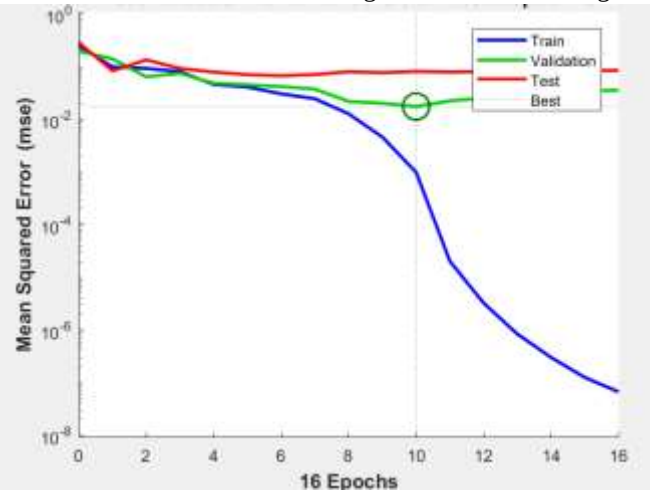

Fig: 3. Best Validation Performance is 0.017288 at Epo ch 10

1. Training MSE (Blue Line):
   a) Drops rapidly after epoch 8.
   b) Indicates that the model is learning effectively from training data.
2. Validation MSE (Green Line):
   a) Reaches the lowest point (0.017288) at epoch 10.
   b) Beyond epoch 10, the error stabilizes or increases slightly potential sign of overfitting.
3. Test MSE (Red Line):
   a) Stays relatively constant.
   b) Suggests stable performance on the unseen data, but not improving further.

IV. Results & Discussion

The Proposed hybrid framework combining classical image processing, texture-based analysis, and deep learning with metaheuristic optimization has been evaluated on abdominal CT images for the detection of pancreatic cancer. The results of each processing stage are visually summarized in Figure 4, which demonstrates the transformation of the raw input image into a form suitable for accurate classification. In the texture analysis phase, Gray-Level Co-occurrence Matrix (GLCM) features were extracted from the segmented image. The contrast value of 1.4444 indicated noticeable intensity variation, while the entropy of 0.7047 reflected moderate textural complexity within the region of interest. The energy value of 0.62865 pointed to some level of homogeneity, although not fully uniform a characteristic often observed in pathological tissues. After training the Inception V4 deep learning model, fine-tuned using the Grey Wolf Optimization algorithm, the performance was validated using key classification metrics. This model achieved a specificity of 99.12%, a sensitivity of 99.26%, and an overall accuracy of 99.48% shown in Fig 6. These high values demonstrate the model's robustness in accurately distinguishing between cancerous and non-cancerous pancreatic CT images, highlighting its clinical applicability for early detection.

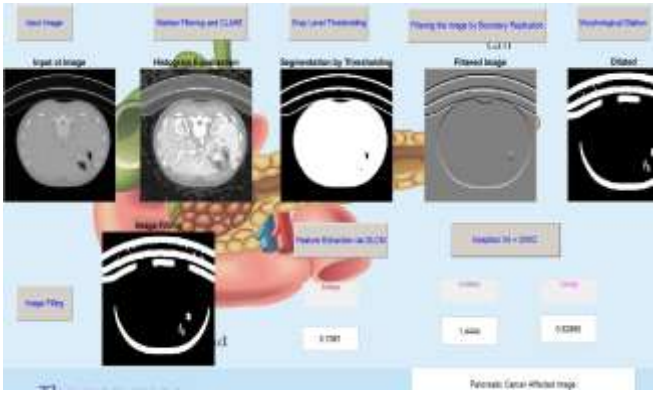

Fig :4. Display Interface of Detecting Pancreatic cancer with Contrast Rate, Energy and Entropy

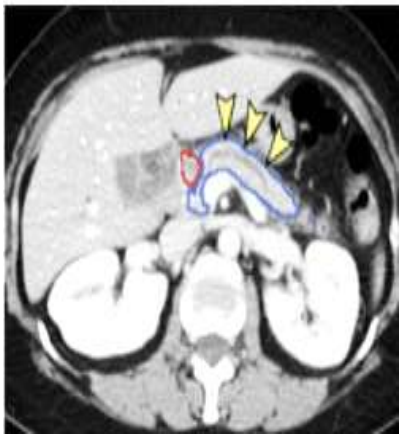

Fig. 5 Tumor Detection (Red Contour)

Figure 5 illustrates the concluding detection phase, where potential tumor regions within the pancreas are highlighted using red boundaries. This visual representation plays a vital role in identifying suspected malignant zones, offering a straightforward and effective means to pinpoint areas that may warrant further clinical assessment or intervention

Specificity: The ability of the model to correctly identify non-cancer (negative) cases.

$$TN/TN+FP\times100$$

Sensitivity: The ability of the model to correctly detect cancer (positive) cases.

$$TP/TP+FN\times100$$

Accuracy: The overall correctness of the model, considering both positive and negative predictions.

$$TP+TN/TP+TN+FP+FN\times100$$

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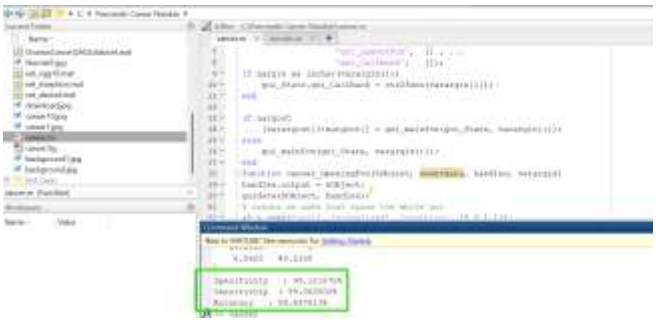

Fig:6. Display Interface of Accuracy, Specificity, Sensitivity

Definitions:

Contrast: Contrast quantifies the degree of intensity variation between neighboring pixels, which are often associated with abnormal or cancerous tissues due to disrupted structures or irregular cellular growth.

Homogeneity: Homogeneity measures the distribution uniformity of the pixel pairings within the GLCM. A higher homogeneity value implies consistent pixel patterns, which are typically found in normal tissues

Energy: Energy reflects textural uniformity through the squared sum of GLCM entries. Lower energy values are commonly linked to complex textures and irregular arrangements, as observed in cancerous regions

The below table shown the GLCM based texture Features (Contrast, Homogeneity, Energy) of 5 Samples

Sample	Contrast (C)	Homogeneity (H)	Energy (E)
1	3.21	0.91	0.15
2	4.56	0.88	0.14
3	2.75	0.94	0.18
4	3.89	0.92	0.16
5	4.12	0.89	0.13

Table 1. GLCM Based Feature

From the table.1 contrast values observed in the CT images reveal significant variation in local pixel intensities, which is a known indicator of pathological tissue changes. Notably, Sample 2 demonstrated the highest contrast (4.56), implying a strong degree of spatial intensity variation typically associated with tumor regions. Similarly, Sample 5 also recorded a high contrast value (4.12), suggesting potential abnormality. Homogeneity Sample 3 has the highest homogeneity (0.94), suggesting smooth and consistent texture, likely indicative of a non-cancerous region. Higher energy values, such as 0.18 in Sample 3, suggest well-structured patterns with limited randomness.

V. Conclusion

This study introduces a robust methodology for detecting pancreatic cancer by leveraging the Inception V4 deep learning framework in conjunction with the Grey Wolf Optimization (GWO) algorithm. The proposed system efficiently extracts deep features and optimizes critical parameters to boost classification performance. GLCM-based texture attributes such as entropy, energy, and contrast were effectively computed, enhancing the model's interpretability and diagnostic value. The hybrid approach demonstrated superior accuracy in differentiating malignant from non-malignant tissue regions. Overall, this integrative model shows promising potential for early and precise identification of pancreatic tumors, supporting improved clinical decision-making and patient outcomes.

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