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STARFISH OPTIMIZATION ALGORITHM TUNED DEEP LEARNING MODELS FOR PANCREATIC DUCTAL ADENOCARCINOMA DETECTION

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Abstract

A Pancreatic Ductal Adenocarcinoma (PDAC) is a malignant neoplasm that significantly jeopardizes patient survival. Artificial classification presents practical challenges, including inconsistent classification accuracy, a substantial effort, and reliance on the clinician's subjective judgment during diagnosis. As pancreas is a complex anatomical structure, it is difficult for a system to process and the related studies are minimal for detecting PDAC. Hence, this paper provides an intelligent strategy for preoperative tumor identification with a Deep Learning (DL) model optimized by the Starfish Optimization Algorithm (SFOA). Various pre-trained DL models, including MobileNetV3, EfficientNetB0, VGG16and ResNet50V2 are examined and the performance of every model is analyzed. The SFOA with CNN demonstrates an accuracy of 97.5% and an improved F-measure rate of 97.54%.

Keywords – PDAC, deep learning, classification, SFOA.

INTRODUCTION

The pancreas, a vital organ in the human body, performs both internal and exterior secretion functions and is prone to numerous illnesses. Pancreatic Ductal Adenocarcinoma (PDAC) is a very aggressive neoplasm of the digestive system that poses significant difficulties in both early detection and subsequent therapy. Although pancreatic cancer is rare in India, its incidence rates are currently rising due to dietary and lifestyle modifications. In India, pancreatic cancer ranks 24th with 10,860 new cases (1.03%) and 18th in fatality rates [1]. The frequency of pancreatic cancer is increasing, making it one of the deadliest malignancies globally.

This critical circumstance underscores the imperative for precise pancreatic cancer identification in medical diagnostics and treatment, essential for the progression of customized medicine and monitoring treatment effectiveness [2,3]. The primary problem is the earlier identification of

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pancreatic cancer, as the illness is typically diagnosed at advanced stages [4]. Patients with early-stage illness are treated successfully with radiotherapy, surgery, and chemotherapyremains extensively disseminated. Consequently, a comprehensive understanding of the risk factors for pancreatic cancer and early diagnosis holds significant potential to decrease overall mortality and enhance patient survival rates [5-7].

The incidence of pancreatic cancer is far lower than that of other cancer types, such as colorectal, lung, and breast cancer [2]. The risk of pancreatic cancer was assessed over an extended period using clinical risk factors, familial history, genetic susceptibility, circulating biomarkersand behavioral influences. The imaging modalities now employed in the diagnosis of pancreatic cancer include Computed Tomography (CT), Magnetic Resonance Imaging (MRI) / Magnetic Resonance Cholangiopancreatography (MRCP),Positron Emission Tomography (PET) and Laparoscopy (LAP) [8,9].

- CT: It is the prevalent imaging modality for numerous patients owing to its affordability and extensive accessibility [10].
- MRI: It exhibits significant sensitivity in identifying hepatic metastases from pancreatic cancer. Nevertheless, it requires significant expense, limited spatial resolution, and much experience. Consequently, MRI has not evolved into a commonly utilized imaging modality in comparison to CT [11]. MRCP can visualize the pancreatic duct system through a non-invasive delineation technique for expert analysis; nonetheless, its diagnostic accuracy remains contentious [12].
- PET : This is the frequently employed to detect distant metastases and assess therapy efficacy, offering extensive anatomical coverage. Nonetheless, its drawback is low spatial resolution [11]. PET is presently not advised, as it fails to provide information regarding pancreatic cancer staging.
- LAP: It is mostly employed to validate examination findings [13].

CT is the primary imaging modality utilized for the evaluation and identification of PC; however, the diagnostic efficacy of this approach relies on the radiologist's expertise [4]. Furthermore, approximately 40% of tumors smaller than 2 cm avoid detection by CT, highlighting an essential need for innovative methods to enhance radiologist interpretation and increase sensitivity in the analysis of pancreatic cancer. Despite the availability of improved imaging tools, detecting pancreatic cancer remains exceedingly difficult, due to the low contrast of the pancreatic lining and the pancreas's variable size and diminutive form in CT scans. Consequently, an automated system for the identification and classification of pancreatic cancer must effectively address these issues, while achieving enhanced accuracy and F-measure rates.

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Considering these points into account, this work presents a fine-tuned deep learning modelfor pancreatic cancer detection and classification. Custom Convolutional Neural Networks (CNN) with four different pre-trained models are MobileNetV3, EfficientNetB0, VGG16, and ResNet50V2 are employed for classification.The Starfishoptimization algorithm (SFOA) is employed for hyperparameter tuning. The tuned CNN is evaluated by several performance measures such as accuracy, precision, recall and F-measure rates. The major contributions of this work are presented as follows.

- A fine-tuned CNN model is presented for PDAC, while exploring four different pre-trained models.
- The hyperparameters are tuned by SFOA to achieve better performance.
- Achieved better accuracy rate of 97.5% in reasonable iterations, which makes the work efficient and promising.
- Different performance measures are employed to assess the performance of the proposed approach, along with k-fold cross validation.

The remainder of this work is organized as follows. Section 2 reviews the recent literature concerning pancreatic cancer detection and classification, while the proposed work is explained in section 3. The performance of the proposed work is evaluated in section 4 and the article is concluded in section 5.

REVIEW OF LITERATURE

This section reviews the state-of-the-art literature concerning pancreatic cancer detection and classification.

In the field of DL, CNNsplay a crucial role in the direct extraction of information from individual images. Contemporary deep learning techniques have achieved state-of-the-art results in the pancreatic segmentation difficulties that they have been studying. As a result of the fact that they enable direct learning from imaging data, these methods have the potential to improve the accuracy and efficiency of pancreatic segmentation, which could lead to enhanced diagnostics, therapeutic approaches, and overall patient outcomes.

There are a number of CNN-based approaches that have shown promising results in the execution of pixel-level labeling tasks for semantic segmentation [14-18]. These methodologies include deep CNNs, VoxResNet, SegNet, fully convolutional networks (FCNs), and U-Net. The precision and effectiveness of segmentation are improved through the utilization of these methods, which make use of a variety of structures and procedures, such as skip connections, pooling, and upsampling. A contracting path and an expanding path are utilized by the U-Net in order to accomplish the tasks of feature extraction and localization. In order to efficiently capture both spatial and temporal

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information, the VoxResNet architecture incorporates residual learning with a three-dimensional convolutional neural network.

An automated framework for the detection of PDAC was developed by the authors of [19] by the application of a contemporary DL technology. The authors placed particular emphasis on the detection of minor lesions. For the purpose of training a nnUnet for automatic cancer detection and segmentation (nnUnet+T), the PDAC is considered to be appropriate. These two additional nnUnet models are trained to investigate the influence of anatomical combinations: (i) segmentation of the tumor, pancreas, and numerous anatomical features that are located in the surrounding area (nnUnet+MS), and (ii) segmentation of the tumor and pancreas (nnUnet+TP).

Within the context of [20], the authors concentrate on the efficient classification and segmentation of pancreatic cancer by the application of a deep learning approach, with the following procedural stages being followed: For the analytical methodology, (i) magnetic resonance imaging (MRI) images obtained from reputable clinics were utilized. (ii) Initially, the raw images were subjected to pre-processing by means of a boosted anisotropic diffusion filter (BADF) and CLAHE techniques. (iii) Subsequently, the segmentation method was utilized to delineate the nodules by employing the FCM clustering (DMFCM) approach. (iv) The features were extracted using HHO-related support vector machine (SVM) prior to being selected.

The authors of [21] used a deep learning technique known as the CNN approach to predict pancreatic cancer images. These images were then processed with the Gaussian Mixture Model (GMM) and the Expectation-Maximization (EM) algorithm. The goal of this process was to identify significant features in CT scans and estimate the percentage of cancer dissemination from the pancreas based on threshold factors that were identified as markers.

A Hierarchical Convolutional Neural Network (H-CNN) that is based on deep learning is proposed by the authors of [22] for the purpose of identifying people according to their classification. In addition, the H-CNN training and setup objectives are intended to improve the effectiveness of the PC picture segmentation process. A CNN methodology that makes use of ResNet-50 was constructed by the authors [23] in order to differentiate between MCN and SCN information. For the purpose of improving the quality of training datasets and increasing the total number of datasets, data augmentation is utilized. Through the completion of the pre-training phase in transfer learning (TL) and the selection of specific layers for training, it is possible to employ training strategies that have been meticulously adjusted.

A novel Multi-modal Fusion and Calibration Network (MFCNet) for tumor segmentation based on three-dimensional quantitative positron emission tomography data is presented by the authors in [24]. At the same time as the remaining design was being introduced, a Multimodal Fusion Downsampling Block (MFDB) was also being introduced. It was demonstrated that the MFDB

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fuse exhibited a feature that was complementary to multimodal images while also maintaining the individual properties of various modal images. In addition, the technique that is dependent on the Multimodal Mutual Calibration Block (MMCB) that is contained inside the inception framework was developed additionally.

A computer-aided diagnosis (CAD) methodology is investigated in [25] by employing Synergic Inception ResNet-V2, a Deep Convolutional Neural Network (CNN) architecture, for the detection of PC cases in publicly accessible CT images. This eliminates the requirement for graphical utilities in medical analysis prior to pathogenic evaluation, thereby saving valuable time for disease prevention. [26] presents a method that makes use of deep neural networks (DNNs) in order to produce autonomous segmentation of pancreatic GTV. This approach is based on multi-parametric magnetic resonance imaging (MRI). An architecture for a CNN that was built on a square window and contained three convolutional layer blocks was utilized by the authors.

Motivated by these existing works, this article aims to present an automated pancreatic tumor detection and classification system based on optimized deep learning model, as described in the following section.

PROPOSED SFOA OPTIMIZED DEEP LEARNING MODEL BASED PANCREATIC TUMOR DETECTION AND CLASSFICATION

This article aims to detect and classify the pancreatic tumor by employing several significant phases such as image acquisition, pre-processing, feature extraction and classification. The feature extraction and classification processes rely on four different deep learning models with hyperparameter tuning. Finally, the performance of the proposed work is assessed by different performance measures against several state-of-the-arttumordetection techniques and the results are discussed. The overall flow of the proposed work is depicted in figure 1.

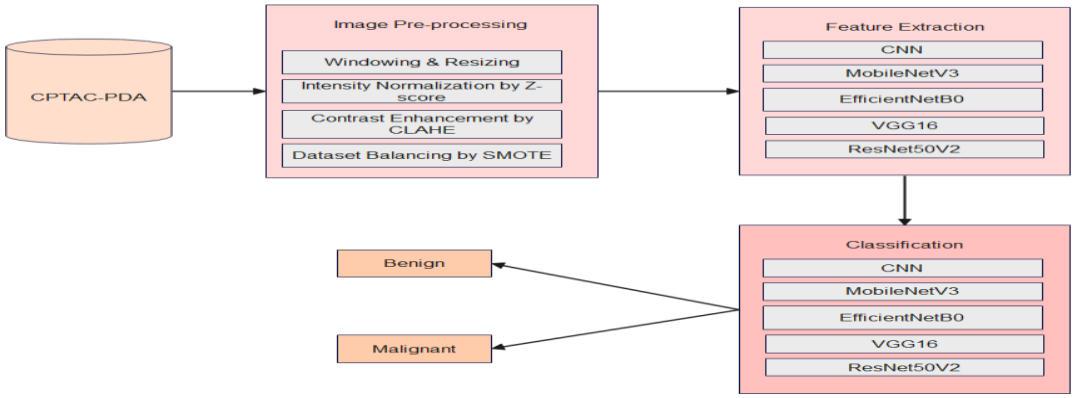

Fig.1. Overall flow of the proposed PDAC classification system

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3.1 Image Acquisition

The CT images are collected from the cancer imaging archive [27], which contains PDAC images of about 168 humans under radiology and pathology streams with 1,32,852 across 1133 series.This workconsiders 10,000 CT images of 118 subjects under radiology stream combined with clinical data, which are in DICOM and CSV formats respectively. Out of 118 subjects, 38 cases are affected by PDAC and the remaining are normal.DICOM format provides numerous benefits over classical image formats in the healthcare domain. These images contain metadata, which includes image acquisition and modality details along with time. The diagnostic quality of the images is pretty good, which is essential for decision making. The size of the image is

3.2 Image Pre-processing

Pre-processing is an important phase of any image processing activity and it plays a crucial role for intricate detailed images. Additionally, the DICOM images contain several information and hence, exclusive pre-processing is necessary. This work involves different pre-processing activities such as image windowing and resizing, intensity normalization and contrast enhancement. The intensity of images is normalized by Z-score technique and the Contrast Limited Adaptive Histogram Equalization (CLAHE) is employed for contrast enhancement.

- **Windowing** : On the other hand, image windowing improves the visibility of subject of interest by adjusting the intensity range, while eliminating the irrelevant intensity ranges.
- **Image resizing** : Image resizing helps in achieving standard size of all input images by altering the spatial dimensions, which helps in minimizing the computational cost.
- **Intensity normalization** : The z-score normalization is carried out for normalizing the intensity, which transforms the pixel values by the following equation.
    - $I_n = \frac{pv-\mu}{\sigma}$ (1)

  pv, μ and σ indicate the pixel value, mean and standard deviation respectively. The purpose of this process is to standardize the distribution of pixels on all images, which in turn helps the classification models to converge quickly, while ensuring reliability. Z-score technique is chosen by this work, as it does not require any prefixed ranges and is ideal for deep learning techniques.
- **Contrast enhancement** : This is performed by CLAHE, which enhances an image across regions rather than global processing. For every region, histogram equalization is carried out and the noise over-amplification is avoided by limiting contrast amplification within a fixed clip range. The adjacent regions are interpolated to eliminate false boundaries.All the image pre-processing activities are represented in figure 2.
- **Dataset balancing** : Balancing a dataset is necessary, as the classifiers are usually biased towards the class with majority samples (benign here). Hence, this issue is addressed by

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oversampling technique Synthetic Minority Over-sampling Technique (SMOTE), which increases the malignant samples by generating synthetic samples. It chooses a malignant sample and determines its neighbours followed by generating synthetic samples. This is accomplished by performing interpolation between the sample and its neighbours, such that exact copies of samples are not possible. In this dataset, there are only 38 tumor cases and the remaining are normal. Hence, the malignant class is oversampled to 80 for balancing the class distribution.

The so pre-processed images are thentreated by feature extraction phase, which acts as a base for classification.

3.3 Deep Feature Extraction

CNNs do not require prior knowledge for carrying out feature extraction from the images and they can process any kind of images. Additionally, CNNs can detect even the finer local features irrespective of the size and scale of images. A standard CNN involves two significant phases such as feature extraction and classification. In the feature extraction process, a feature map that highlights different aspects of images is produced. This work explores four different pretrained DL models such as MobileNetV3, EfficientNetB0, VGG16, and ResNet50V2.The details of all the DL models are presented in Table 1.

Table 1. Details of DL models

DL Model	Advantage	Disadvantage
MobileNetV3	Lightweight and speed	Underfitting in some cases
EfficientNetB0	Good scaling	Difficult to fine-tune
VGG16	Better understandability	Computational Complexity
ResNet50V2	Stability	More parameters

MobileNetV3 is a lightweight but efficient DL model, which is found to computationally efficient with good accuracy rates. EfficientNetB0 processes the input images, in order to obtain feature vectors with rich information. Several distinct features are collected from the images at a minimal computational cost with low resource requirements. It provides a 1280dimensional feature vector that is capableof differentiating between classes. VGG16 can effectively capture hierarchical visual features and provides stability. VGG16 is high dimensional and works well with medical images. ResNet50V2 is an improved version of ResNet architecture that can maintain semantic information and free from training inefficiency. Expressive high-dimensional feature vectors are extracted to make it effective for classification and are highly suitable for medical images.

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3.4 Tumor Classification

The classificationphase of this work employs the same DL models for attaining better accuracy rates. Two dimensional convolutional, max-pooling and dropout layers form the base of this model, while a global average pooling layer minimizes the size of data without compromising on the information. Three interconnected dense layers with sigmoid and ReLu activation functions involve in final decision making with Adam optimizer at a learning rate of 0.0005. The size of the input image is with 3 as kernel size, 18 and 20 are the values of batch size and epochs. The size of epoch is selected in such a way to avoid overfitting or underfitting issues. The hyperparameters are tuned by Starfish Optimization Algorithm (SFOA) for achieving better performance of the classification model [28].

The SFOA starts with a random solution and is refined through the iterations. The working strategy of any optimization algorithm relies on a fitness function. The SFOA is summarized in the following subsection.

3.4.1 SFOA

SFOA imitates the behavior of StarFish (SF) and designed in a way to deal with complex optimization problems. Some of the interesting behaviors of SF are taken into consideration for exploring and reaching the optimal solution. Central coordination, tube feet and arm like movements, foraging with chemotaxis and information sharing are the distinct characteristics of SF. All these phases are briefed in the following parts.

3.4.1.1 Initialization

In the beginning, a population of SF is generated and each SF is a vector denoted by $X_i \in R^d$, where d is the parameter count. The SF are randomly distributed within the assigned limits and the fitness values of all SF are determined by the following function.

$$X_i^0 = LB + rand() \cdot (UB - LB) \quad (2)$$

In the above equation, UB and LB indicate upper and lower bounds respectively, while $rand()$ is a random number between 0 and 1.

3.1.1.1 Central disc coordination

The central disc of a SF is utilized to control the tube feet and arms. In this stage, a SF is selected with the best fitness score such that the movement of other SF toward or farther from the central solution is impacted. The search balance between exploration and exploitation is adjusted here to bring in adaptive convergence.

3.1.1.2 Local exploration (Tube feet movement)

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This phase imitates the random and little movements of the tube feet of SF. Small perturbations in the SF's current position are generated for local exploration. This activity helps in tuning the solutions near the current position, which is given by eqn.(3).

$$X_i^{new} = X_i + \alpha \cdot (rand() - 0.5) \quad (3)$$

Here, α controls the range of movement and is a step-size coefficient.

3.1.1.3 Global exploration (Arm movement)

This stage simulates that the arms of SF move to probe different areas by moving closer and farther to the best SF. It supports to avoid local optima and to diversify the search.

$$X_i^{new} = X_i + \beta \cdot (X_{best} - X_i) + \gamma \cdot (rand() - 0.5) \quad (4)$$

In the above eqn., β and γ are exploration coefficients and X_{best} is the optimal position of the SF.

3.1.1.4 Chemotaxis behavior (Foraging)

Food sources are detected by SF by means of chemical gradients. When a SF finds any better fitness in a direction, then it amplifies that direction, which helps it to detect better solutions. It is represented by the following eqn.

$$iff(X_i^{new}) < f(X_i): X_i = X_i^{new} \quad (5)$$

This state allows movements only to enhance its fitness.

3.1.1.5 Memory sharing

The position of every SF is updated based on the above stated movements such as central disc, tube feet and arm. The best positions are updated by the SF across the swarm and is represented by

$$X_i^{t+1} = X_i^t + w_1 \cdot TFM + w_2 \cdot ARM + w_3 \cdot CHEM \quad (6)$$

Where TFM, $ARM, CHEM$ denote tube feet movement, arm and chemotaxis update vectors respectively, while w_1, w_2, w_3 are weights.

3.1.1.6 Convergence and outcome

These steps are processed continuously till it reaches the termination criteria such as reaching the maximum iterations, target achievement and impossible enhancement over N iterations. Finally,X_{best} is returned as the output.

The main advantages of SFOA are its combined local and global search policy, its ability to work well over complex problems, better parameter handling, efficient avoidance of premature convergence, parallel search mechanism and high suitability for CNN optimization and feature selection in medical image analysis.

3.5 Hyperparameter Tuning

Hyperparameters are variables to be trained such that they are in a specific range and manual setting requires more time and knowledge. Hence, the support of optimization algorithm helps in rendering the best value for the hyperparameter and the choice of optimization algorithm plays a vital role in the hyperparameter determination. The SFOA performs well and the classification efficiency proves the performance of it.

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The learning rate controls the change in model's weight during training. The learning rate is varied in between the range of 0.0001 to 0.0005. Smaller learning rate results in slower convergence and may trapped by local minima and the larger learning rate overshoots the minima. Thus, optimal learning rate is needed to be chosen. Epoch range is set between 5 and 30, which determines the count of data traversal during model training. When the epoch count is optimal, it results in minimal validation and training loss, while maintaining good accuracy rates.

Dropout is a regularization parameter that ignores some neurons in a random fashion during training, which influences the model's accuracy and generalization. Optimal dropout rate helps to avoid under and overfitting, while achieving better training and validation accuracy rates and is set between 0.2 and 0.5.Dense layer neurons indicate the count of neurons in the dense layer that supports in understanding intricate patterns. This work explores the range between 128-256, in order to process the data effectively. Kernel size is an important parameter and is directly influences on the complexity of the model, feature abstraction and so on. It defines the size of spatial window that the convolutional operation employs, while scanning the image. The kernel size employed by this work ranges between 3 and 5. The parameters chosen by this work along with the accuracy rates are shown in table 2. The experimental results attained by this work are discussed in the following section.

RESULTS AND DISCUSSION

This work is simulated using MATLAB 2021A on a stand-alone system with 16 GB RAM and Intel i7. The train/test ratio is fixed as 70/30, as it attained better results. The DL models are trained by varying the hyperparameters and the results are shown below. Sample input images are shown in figure 2.

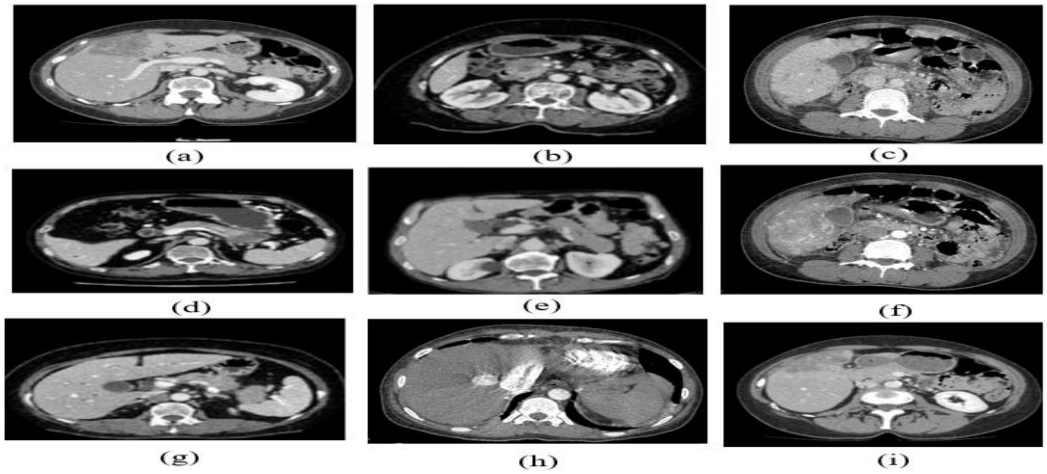

Fig.2. Sample input images

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To evaluate the efficacy of the work, standard performance criteria are employed. The measures encompass accuracy (∂), precision ($\wp$), recall ($\Re$) and F-score ($\mathcal{F}$). The efficacy of the work under discussion is assessed utilizing equations (5-9). ∂ represents the proportion of correctly classified diseased samples to the total number of diseased samples. $\wp$ denotes the ratio of accurately predicted positive occurrences to the total number of anticipated positive samples.

$$\partial = \frac{T_{Pos}+T_{Neg}}{T_{Pos}+T_{Neg}+F_{Pos}+F_{Neg}} \quad (5)$$

$$\wp = \frac{T_{Pos}}{T_{Pos}+F_{Pos}} \quad (6)$$

$$\Re = \frac{T_{Pos}}{T_{Pos}+F_{Neg}} \quad (7)$$

$$\mathcal{F} = 2 \times \frac{(\wp \times \Re)}{(\wp + \Re)} \quad (8)$$

The proportion of positive samples that were accurately recognized in comparison to the total count of samples that were indeed positive is represented by $\Re$, which is frequently referred to as the sensitivity or true positive rate. The harmonic mean of $\wp$ and $\Re$ is used to ascertain the value of $\mathcal{F}$. The MCC is a statistical metric that is employed to quantify the degree of correlation between forecasts and observations. It produces a value that can fluctuate between -1 and +1, taking into consideration both true and false positives, as well as negatives.The chosen hyperparameters and their corresponding accuracy rate are shown in Table 2.

Table 2. Hyperparameters of the DL models (i=10)

Model	LR (ADAM)	Dropout	Dense Layer	Epoch	Kernel Size	Accuracy
SFOA-MobileNetV3	0.00034	0.3468	58	20	4	0.90
SFOA-EfficientNetB0	0.00037	0.4867	54	11	3	0.87
SFOA-VGG16	0.00046	0.3861	26	19	3	0.81
SFOA-ResNet50V2	0.00028	0.2756	29	23	4	0.84

The following table 3 shows the performance outcomes of the proposed work.

Table 3. Performance results

Model	LR (ADAM)	Dropout	Dense Layer	Epoch	Kernel Size	Accuracy

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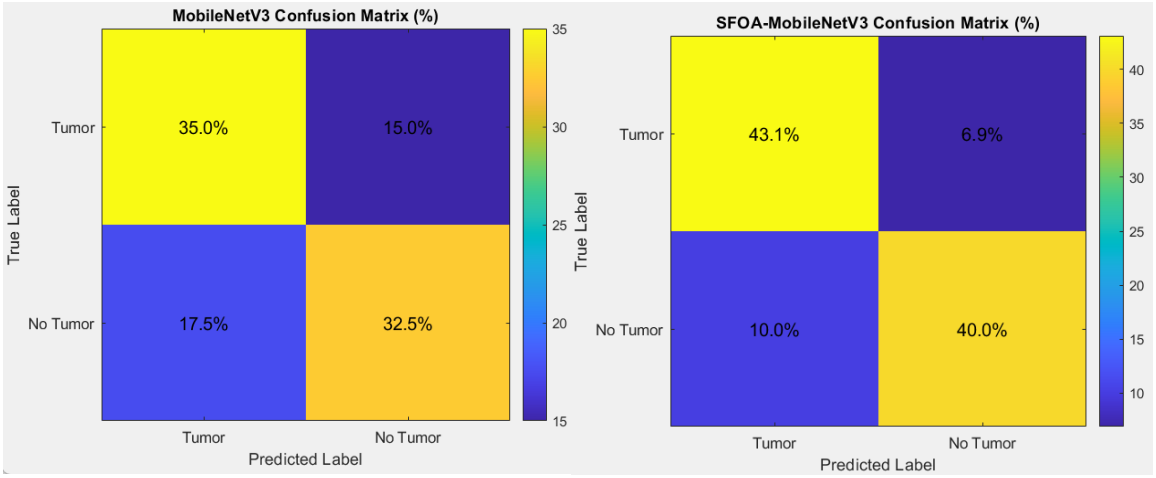
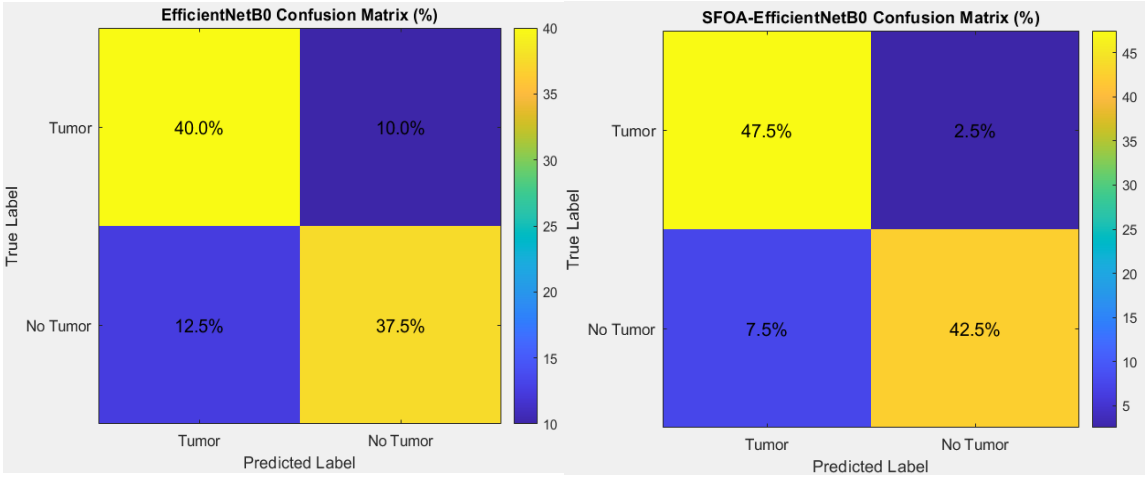
SFOA-VGG16	0.00046	0.3861	26	19	3	0.81
SFOA-ResNet50V2	0.00028	0.2756	29	23	4	0.84

The confusion matrices of all the DL models with and without optimization are shown in figure 3.



(a) (a1)



(b) (b1)

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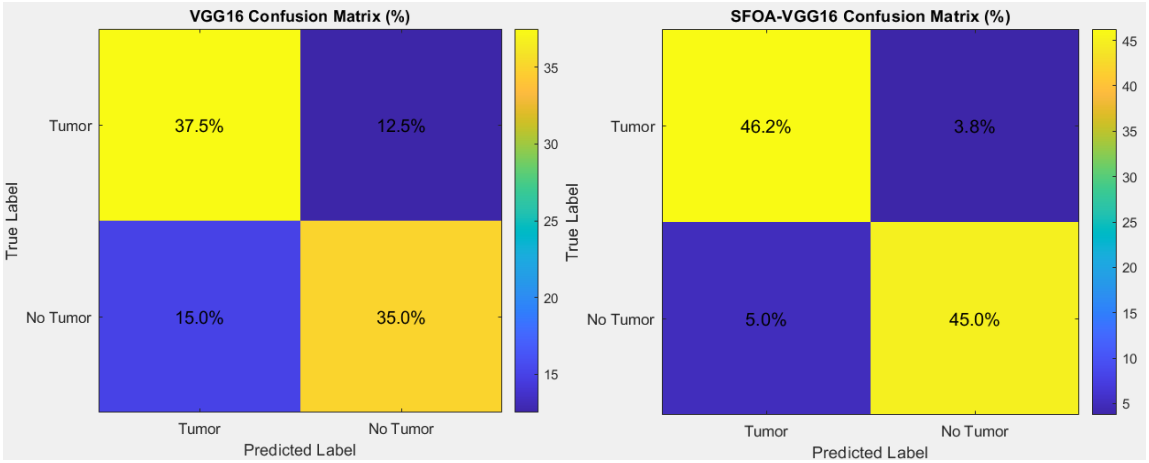
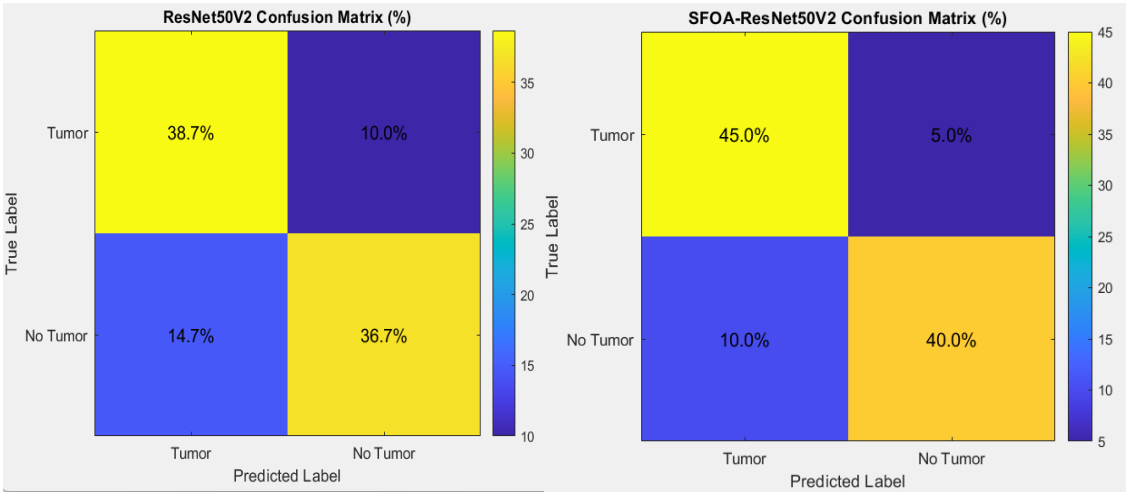
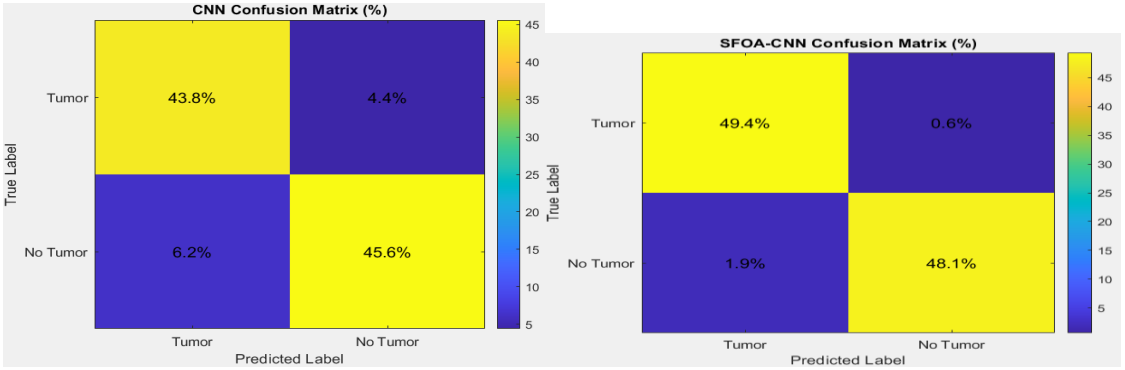


(c) (c1)



(d) (d1)



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(e) (e1)

Fig.3. Confusion Matrices of DL models (a1) CNN (b) MobileNetV3 (c) EfficientNetB0 (d) VGG16 (e) ResNet50V2 (a1) CNN (b1) SFOA-MobileNetV3 (c1) SFOA-EfficientNetB0 (d1) SFOA-VGG16 (e1) SFOA-ResNet50V2

From the figure, the SFOA performs well in tuning the hyperparameter and the performance significantly improves in all the models. However, the performance of SFOA-CNN outperforms the other DL models. The overall performance of the study is depicted in figure 4.

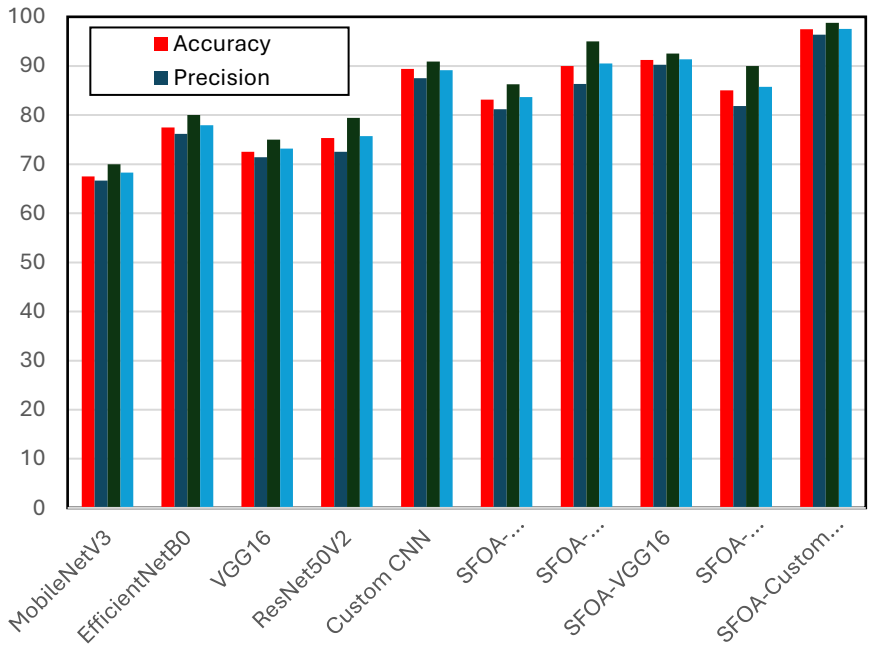

Fig.4. Performance of DL models in detecting tumor

K-fold cross-validation, a technique for evaluating machine learning models, is also used to examine the findings. Because it lowers variance and enhances model generalization performance estimates, this type of validation is usually used when there is a lack of data, but it can also be useful when there is adequate data. It operates by breaking the data up into "k" subsets, and then using a varied fold as the test set to train the model "k" times. The model's performance is assessed by averaging its performance metrics over "k" runs.In k-fold cross-validation, the parameter "k" determines the number of folds.

A higher "k" number indicates a more accurate performance evaluation, because more data is used for testing and validation. Because the model needs to be trained and assessed multiple times, increasing "k" increases the evaluation's computing overhead. A larger "k" may require more resources and jeopardize model development or evaluation. In these situations, balancing ∂ and

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computing expense may be achieved by setting 'k' to 5. This is less computationally intensive, but requires fewer model iterations, therefore the results might not be as accurate as with a larger "k". Table 4 shows the results attained by the proposed model for fold 5.

Table 4. Cross validation results with ‘k=5’

Model	∂(%)	$\wp$(%)	$\Re$(%)	$\mathcal{F}$(%)
SFOA-MobileNetV3	80.6	78.6	82.05	80.31
SFOA-EfficientNetB0	83.4	80.2	94.6	86.71
SFOA-VGG16	84.9	81.4	89.7	85.34
SFOA-ResNet50V2	81.8	80.65	87.9	84.10
SFOA- CNN	**94.8**	**92.7**	**93.8**	**93.23**

The cross-validation results strongly prove the efficacy of SFOA-CNN model, in contract to the other comparative models.The main reason for the performance of this work is effective pre-processing of input images, which makes the subsequent processes effective. The employment of SFOA better tunes the DL models, which further enhances the learning rate with better accuracy. The main goal of this work is to attain minimal FP and FN rates, as both cause serious effects on the patient, which is attained in reasonable epochs.

CONCLUSIONS

This article presents an automated PDAC classification system based on DL models, which is optimized by SFOA. The major phases involved in this work are data acquisition, pre-processing, feature extraction and classification. Data acquisition is challenging, as the works related to PDAC classification is limited. Different operations are carried out in pre-processing step, where the images are windowed, resized, contrast enhanced, intensity normalized and balanced class distribution. In the dataset, the malignant class has only few samples, which could result in biased outcome. Hence, the class is oversampled SMOTE method and both the classes are similarly distributed. The deep features are extracted and classified by employing DL models such as CNN, MobileNetV3, EfficientNetB0, VGG16 and ResNet50V2. The hyperparameters of the models are tuned by SFOA and the experimental results are investigated. The results indicate that the SFOA optimized CNN proves better accuracy and F-measure rates of 97% and 97.5%respectively. In future, this work can be extended by considering histopathological images and tumor grading can be done.

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