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Application of Deep Learning on Pancreas Tumor Detection
(Topic Area: Deep Learning)

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Abstract:- This study focuses on the importance of detecting and diagnosing pancreatic tumors accurately to improve patient outcomes. It explores the use of deep learning algorithms, specifically convolutional neural networks, for automated pancreas tumor detection using CT scans. The CT images undergo preprocessing steps such as noise reduction, normalization, and image resampling. These preprocessed images are then used to train a deep learning model that learns the characteristics of pancreatic tumors.

The model is trained using a large dataset of annotated CT images, consisting of both tumor-positive and tumor-negative cases. Various optimization techniques and loss functions are employed to maximize the model's performance. The initial results show promising outcomes, with the model achieving high accuracy in pancreas tumor detection. Its sensitivity and specificity are evaluated to assess its ability to correctly identify tumor presence or absence. The model's performance is further validated using independent testing datasets to ensure its generalizability.

The study aims to develop an efficient and reliable automated system for detecting pancreatic tumors by leveraging deep learning techniques on CT images. This approach has the potential to assist radiologists and clinicians in early and accurate diagnosis of pancreatic cancer, leading to timely treatment interventions and improved patient outcomes.

I. INTRODUCTION

Pancreatic cancer is one of the most deadly forms of cancer, characterized by its aggressive nature and late-stage detection. Timely and accurate identification of pancreas tumors is crucial for improving patient outcomes through early intervention and personalized treatment strategies. Medical imaging techniques, such as computed tomography (CT) scans and magnetic resonance imaging (MRI), have been effective in the detection of pancreatic tumors. However, the interpretation of these images can be challenging and subjective, leading to limitations in accuracy and efficiency.

In recent years, deep learning has emerged as a powerful approach for medical image analysis, showcasing remarkable success in various fields.

Deep learning methods, particularly Convolutional Neural Networks (CNNs), have demonstrated superior performance in object recognition and localization tasks. Consequently, researchers have turned their attention to exploring the potential of deep learning in pancreas tumor detection.

The objective of this study is to investigate the application of deep learning techniques for accurate and automated detection of pancreas tumors using medical imaging data. By leveraging the capability of deep neural networks to learn complex patterns and detect subtle abnormalities, we aim to improve the efficiency and reliability of the detection process. Furthermore, we explore the integration of additional data sources, to enhance the accuracy and efficiency of pancreas tumor detection.

CT images have gained attention as potential non-invasive indicators of various diseases, including pancreatic cancer. The analysis of specific molecules or substances present in urine can provide valuable insights into disease progression and treatment response. Therefore, we aim to investigate CT images with deep learning models to further improve the early detection and monitoring of pancreas tumors. This research holds significant implications for clinical practice and patient care. The development of an accurate and automated pancreas tumor detection system can streamline the diagnostic process, leading to earlier interventions and improved patient outcomes.

II. BACKGROUND OF THE STUDY

Pancreatic cancer is a highly lethal disease, and detecting it at an early stage is crucial for effective treatment. However, manual interpretation of CT scans for tumor detection is a time-consuming and subjective process. Therefore, there is a need for automated methods to assist in the early detection of pancreatic tumors.

Deep learning, a powerful technique in image analysis, has shown great potential in automating the detection of pancreas tumors using CT images. This technique involves training a model to recognize patterns and features that are indicative of tumors. However, there are specific challenges associated with pancreatic tumors, such as their variable sizes and shapes, which need to be overcome for accurate detection.

The main objective of this study is to develop a robust deep learning model that is specifically optimized for the detection of pancreatic tumors from CT scans. This model will utilize advanced neural network architectures and subtle imaging features that are characteristic of tumors in the pancreas. By leveraging these techniques, the model aims to assist radiologists and clinicians in making timely and accurate diagnoses.

The findings of this study have the potential to significantly advance the field of computer-aided diagnosis for pancreatic cancer. An efficient and reliable automated system for tumor detection will not only improve the quality of patient care but also free up valuable time for medical professionals, allowing them to focus on other critical tasks. Ultimately, this research aims to contribute to the early detection and improved management of pancreatic cancer for better patient outcomes.

III. METHODOLOGY

A. Data Collection Methods and Instruments/ Tools

Data collection is the practice of gathering information using specified procedures in order to react to the study's predetermined research subject is known as data collecting. In this study, the researcher used mixed method (both qualitative and quantitative) and examined secondary data.

B. Data analysis

This refers to the process of uncovering solutions via study and interpretation. Understanding the findings of surveys and administrative sources, as well as presenting data information, necessitate data analysis. Data analysis is expected to shed light on the study's issue and respondents' perspectives, as well as boost readers' awareness of the topic and encourage their involvement in this aspect of the research. Jupyter notebook and kaggle were employed for the purpose of analyzing the data and show the results using scientific data analysis techniques. (Burns, 2022) **Performance metrics** such as accuracy, sensitivity, specificity, precision (positive predictive value), and **F1 score** can be calculated to assess the effectiveness of deep learning. These **metrics** are commonly used to assess the overall accuracy and effectiveness of deep learning models in detecting pancreas tumor were used as a data analysis technique. Assessing the performance of the deep learning model with and without the integration of biomarkers and Calculating **standard evaluation metrics**, including **accuracy**, and F1 score. Process of discovering solutions through investigation and interpretation is known as data analysis. Understanding survey and administrative source results and presenting data information require data analysis. Data analysis is anticipated to provide light on the subject of the study and the respondents' perceptions, as well as to increase readers' understanding of the subject and pique their interest in this portion of the research. (Burns, 2022).

C. Research Design

This is a strategy or blueprint which shows how data required for the solution of the problem that the researcher focused on, the procedure and methods for data collection and analysis, answered the research questions. In these lines the research herein the present research study, researcher employed a combination of descriptive and correlation research design to describe the characteristics of a population under investigation and carefully examine the use of deep learning models in pancreas tumor detection (Hardt,2016).

Research design involved the following:

- **Objective:** The objective of this research is to investigate the application of deep learning techniques for pancreas tumor detection using CT images. The study aims to develop and evaluate deep learning models for accurate and efficient detection of pancreatic tumors, ultimately contributing to early diagnosis and improved patient outcomes.

➢ *Data Collection:*

- **Dataset selection**: Obtain a dataset consisting of CT images of patients from Rwanda Military Hospital with annotated pancreas tumor labels. The dataset should include a diverse range of tumor sizes, shapes, and locations.
- **Data preprocessing:** Perform preprocessing steps such as resampling, normalization, and noise reduction to enhance image quality and ensure consistency across the dataset.
- **Model Development:**
- **Model architecture:** Design a deep learning model suitable for pancreas tumor detection using CT images. Consider architectures such as convolutional neural networks (CNNs) that can effectively capture spatial information and automatically learn relevant tumor features.
- **Training and validation:** Split the dataset into training and validation sets. Train the deep learning model on the training set using appropriate optimization algorithms and loss functions. Validate the model using the validation set and fine-tune the hyperparameters as necessary.
- **Evaluation Metrics:** Select appropriate evaluation metrics to assess the performance of deep learning models for pancreas tumor detection. Common metrics include sensitivity, specificity, accuracy, precision, and the area under the receiver operating characteristic curve (AUC-ROC).
- **Model Comparison**: Compare the performance of the developed deep learning model with existing state-of-the-art methods or traditional machine learning approaches for pancreas tumor detection. This can help evaluate the effectiveness and superiority of deep learning in this domain.
- **Generalization and Robustness:** Assess the generalization capabilities and robustness of the deep learning model by testing it on an independent test set. Evaluate the model's performance on CT images from different hospitals or datasets to ensure that it can handle variations in acquisition protocols and data sources.
- **Interpretability**: Investigate methods to enhance the interpretability and explainability of the deep learning model. Techniques such as attention mechanisms, saliency maps, or layer-wise relevance propagation can be employed to understand the model's decision-making process and identify regions of interest that contribute to tumor detection.

- **Ethical Considerations:** Ensure compliance with ethical guidelines and data protection policies. Obtain necessary approvals and permissions for using patient data. Anonymize or de-identify the data to protect patient privacy.
- **Results and Discussion**: Analyze the results obtained from the evaluation of the deep learning model. Discuss the model's performance, strengths, and limitations. Compare the results with existing literature and address any challenges encountered during the research.
- **Conclusion and Future Directions:** Summarize the findings of the research and highlight the implications and potential applications of deep learning in pancreas tumor detection. Discuss future directions for research, such as exploring novel architectures, addressing data limitations, or integrating clinical decision support systems.

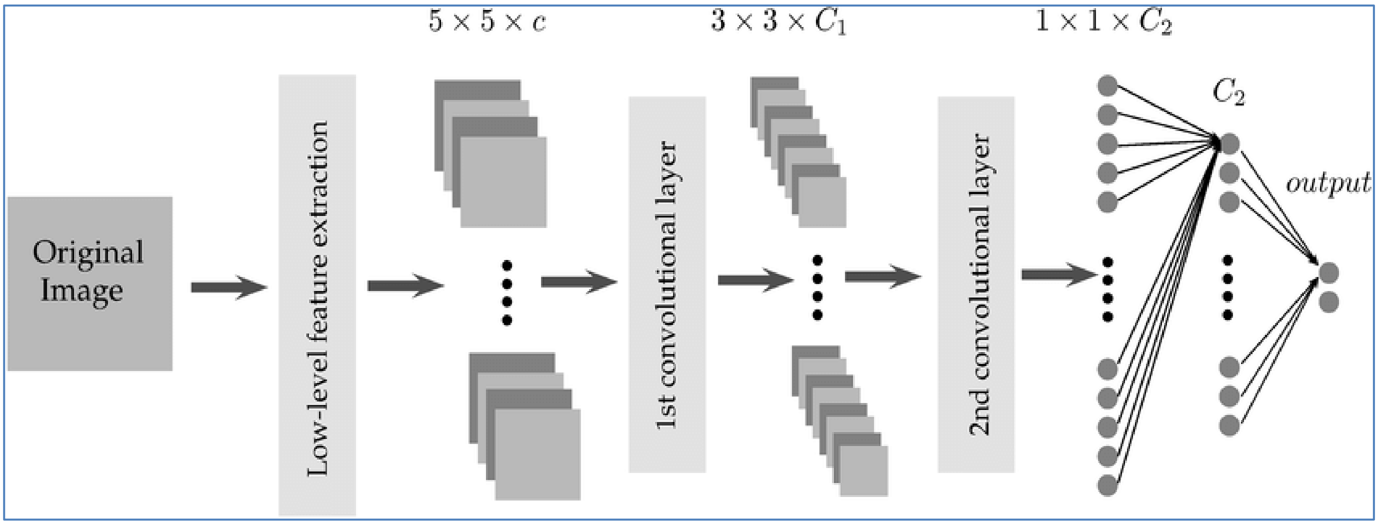

Fig. 1: Deep Learning Model

A conceptual framework is analytical tool with several variations and contexts. It is used to make conceptual distinctions and organize ideas. It provides a general representational of relationship of things in a given phenomenon.

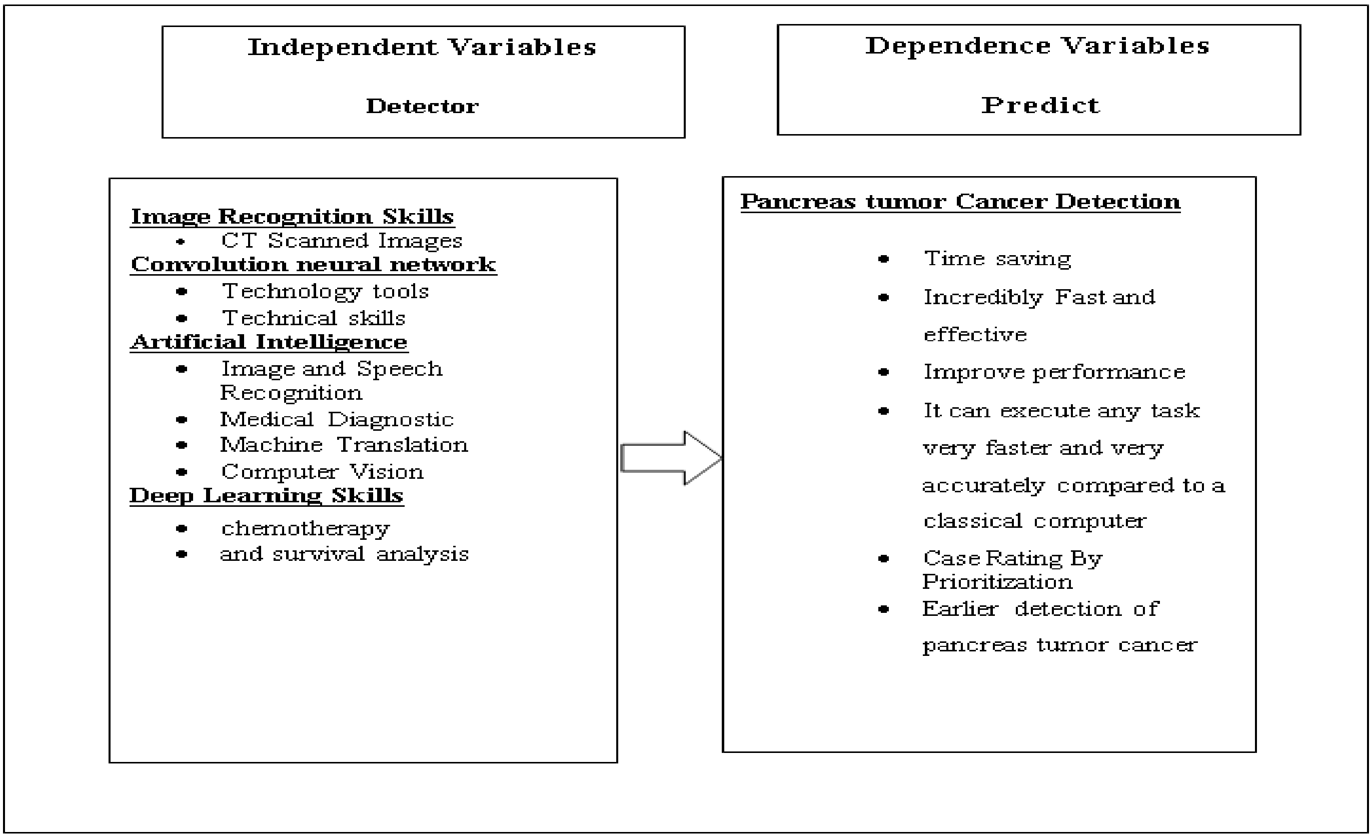

Fig. 2: Conceptual Framework on Pancreas Tumor Detection

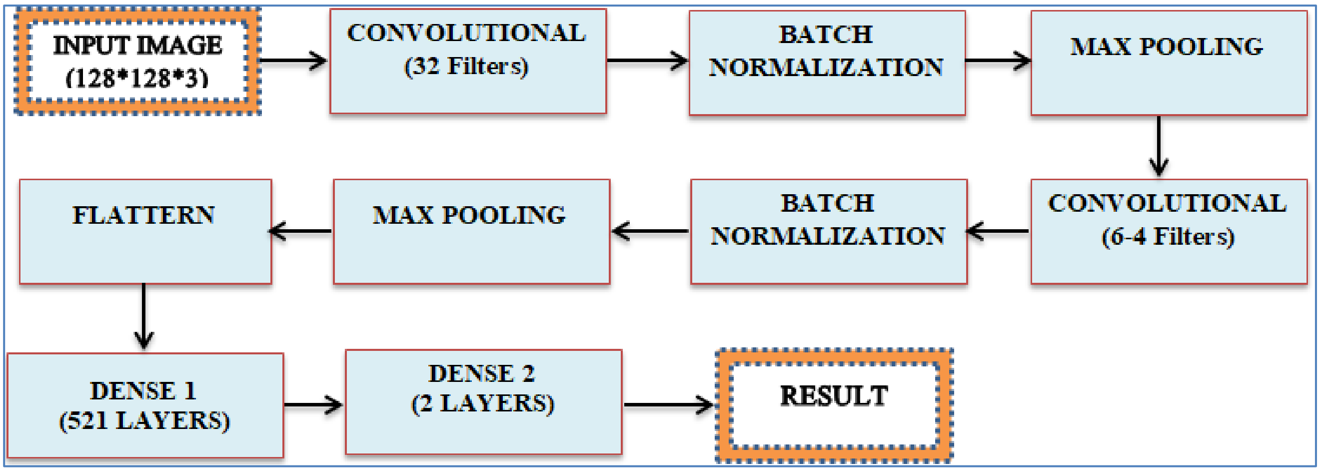

Fig. 3: CNN-based method for detecting pancreas Tumor

IV. DATA PRESENTATION

Steps to involve in pancreas tumor detection:

A. *Importing Necessary Libraries*

Importing necessary libraries in deep learning refers to including or bringing in the required software packages or libraries into your code. These libraries offer pre-implemented functions and tools for developing and using deep learning models. They provide functionalities like data handling, neural network creation, model training, optimization, and performance evaluation. Popular deep learning libraries include TensorFlow, Keras, PyTorch, and scikit-learn. Importing these libraries saves time and effort by utilizing existing implementations, rather than building everything from scratch.

```
[ ] from keras.callbacks import ModelCheckpoint,EarlyStopping
    from keras.layers import Activation, Dropout, Flatten, Dense
    from keras.layers import Conv2D, MaxPooling2D
    from keras.models import Sequential
    from keras.utils import img_to_array, load_img
    from keras.preprocessing.image import ImageDataGenerator
    from sklearn.metrics import classification_report, confusion_matrix,ConfusionMatrixDisplay
    import splitfolders
    import matplotlib.pyplot as plt
    import numpy as np
```

```
In [2]:
    import pandas as pd
    import pycaret
    import seaborn as sns
    import missingno as msno
    import numpy as np
    import plotly.express as px
    from pycaret.classification import *
    sns.set()
    sns.set_context("paper")
    pd.set_option('display.max_colwidth', None)
    import matplotlib.pyplot as plt
```

Fig. 4: Importing Necessary Libraries

B. *Importing Dataset*

This involves loading and incorporating a specific dataset into the deep learning code or environment. It includes fetching the dataset from a source, such as a file or online repository, and preparing it for use in model training or evaluation. This process includes tasks like parsing the data, preprocessing or transforming it, splitting it into training and testing sets, and ensuring compatibility with the chosen deep learning framework. Importing datasets is essential as it provides input for training models and enables effective analysis and learning from the data.

```
[ ] import splitfolders

    input_folder = "/content/Pancreatic_Tumor_Detection/data_pan"

    splitfolders.ratio(input_folder, output='test_train_split', seed=42, ratio=(.7, .2, .1),group_prefix=None)
```

Fig. 5: Importing Dataset

C. Defining the Model

After opening the system you will be required to enter staff identification in way of identifying whose nurses is on duty. After entering your staff id you will be able to register a patient into the system.

This refers to the process of creating the architecture or structure of a neural network. It involves determining the number and type of layers, the connectivity between these layers, and specifying the parameters of each layer, such as the number of neurons or the activation functions to be used. Defining the model also includes establishing the input and output dimensions of the network. By defining the model, deep learning practitioners design the framework that enables the network to learn patterns and make predictions based on the input data.

```
[ ] SIZE = 150
    # 2 conv and pool layers. with some normalization and drops in between.

    INPUT_SHAPE = (SIZE, SIZE, 3)  # change to (SIZE, SIZE, 3)
```

Fig. 6: Defining the Model

```
[ ] model = Sequential()
    model.add(Conv2D(32, (3, 3), input_shape=INPUT_SHAPE,padding='same'))
    model.add(Activation("relu"))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(32, (3, 3)))
    model.add(Activation("relu"))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Conv2D(64, (3, 3)))
    model.add(Activation("relu"))
    model.add(MaxPooling2D(pool_size=(2, 2)))

    model.add(Flatten())
    model.add(Dense(64))
    model.add(Activation("relu"))
    model.add(Dropout(0.25))
    model.add(Dense(1))
    model.add(Activation("sigmoid"))

    model.compile(loss="binary_crossentropy", optimizer="rmsprop", metrics=["accuracy"])

    print(model.summary())

    Model: "sequential"
    _________________________________________________________________
     Layer (type)                Output Shape              Param #
    =================================================================
     conv2d (Conv2D)             (None, 150, 150, 32)      896

     activation (Activation)     (None, 150, 150, 32)      0

     max_pooling2d (MaxPooling2D  (None, 75, 75, 32)       0
     )
```

Fig. 7: Presentation of the Model

D. Data Augmentation

This refers to the technique of artificially expanding a training dataset by applying various transformations to the existing data samples. The transformations include rotations, translations, scaling, flipping, and adding noise or other modifications. The purpose of data augmentation is to introduce variability and increase the diversity of the training data, helping the model generalize better and improve its robustness to different scenarios. By generating new variations of the data, data augmentation aids in preventing overfitting and can enhance the performance of deep learning models.

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```
[ ]  batch_size = 16
```

Fig. 8: Data Augmentation

E. Train Data

Training and data validation are essential components of deep learning. During the training phase, the model learns and adjusts its parameters using a set of labeled training data. The model undergoes multiple iterations or epochs, where it makes predictions, calculates the loss (error), and updates the weights to minimize the loss and improve performance. On the other hand, data validation is the process of evaluating the model's performance and generalization on a separate set of labeled data that was not used for training. This allows the model to be assessed for accuracy, error rates, or other performance metrics. Training and data validation together ensure that the deep learning model learns from data effectively and can make accurate predictions on unseen examples.

```
train_datagen = ImageDataGenerator(
        rescale=1.0 / 255,
        rotation_range=45,
        shear_range=0.2,
        zoom_range=0.2,
        horizontal_flip=True,
)
```

Fig. 9: Train Data

F. Train and Validation Data

```
validation_datagen = ImageDataGenerator(
    rescale=1.0 / 255,
    rotation_range=45,
    shear_range=0.2,
    zoom_range=0.2,
)

train_generator = train_datagen.flow_from_directory(
    "/content/Pancreatic_Tumor_Detection/test_train_split/train",
    target_size=(150, 150),
    batch_size=batch_size,
    class_mode="binary",
)  # since we use binary_crossentropy loss, we need binary labels

Found 987 images belonging to 2 classes.

validation_generator = validation_datagen.flow_from_directory(
    "/content/Pancreatic_Tumor_Detection/test_train_split/val",
    target_size=(150, 150),
    batch_size=batch_size,
    class_mode="binary",
)

Found 282 images belonging to 2 classes.
```

Fig. 10: Train and Validation Data

G. Training Check-points

This refers to saving intermediate snapshots of the model during the training process. These checkpoints capture the model's parameters, optimizer state, and other relevant information at a particular point in time. By saving checkpoints, the training can be paused and resumed later without losing progress. Additionally, these checkpoints enable model evaluation, inference, or fine-tuning at different stages by restoring the model's state. Training checkpoints are crucial for reproducing and sharing models, analyzing training progression, and selecting the best-performing model based on validation metrics.

```
[ ] filepath = "/content/Pancreatic_Tumor_Detection/saved_models/weights-improvement.hdf5"
    es=EarlyStopping(monitor="val_accuracy",min_delta=0.01,patience=5,verbose=1,mode='auto')
    checkpoint = ModelCheckpoint(
        filepath, monitor="val_accuracy", verbose=1, save_best_only=True, mode="max"
    )
    callbacks_list = [checkpoint,es]
```

Fig. 11: Training Check-points

H. Model Training

This refers to the process of optimizing the parameters and structure of a neural network using labeled training data. During training, the model learns to make accurate predictions by iteratively adjusting its weights based on the calculated loss between predicted and ground truth values. This optimization is typically performed using techniques like gradient descent and backpropagation, where gradients are computed and used to update the model's parameters. Through this process, the model gradually improves its ability to generalize and make accurate predictions on unseen data by minimizing the training loss.

```
hs = model.fit_generator(
    train_generator,
    steps_per_epoch=16,
    epochs=30,
    validation_data=validation_generator,
    validation_steps=16,
    callbacks=callbacks_list,
)

C:\Users\dkvhe\AppData\Local\Temp\ipykernel_7928\3872973094.py:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version.
  hs = model.fit_generator(
Epoch 1/30
16/16 [==============================] - ETA: 0s - loss: 0.7276 - accuracy: 0.8320
Epoch 1: val_accuracy improved from -inf to 0.98047, saving model to saved_models\weights-improvement.hdf5
16/16 [==============================] - 8s 446ms/step - loss: 0.7276 - accuracy: 0.8320 - val_loss: 0.1053 - val_accuracy: 0.9805
Epoch 2/30
16/16 [==============================] - ETA: 0s - loss: 0.2282 - accuracy: 0.9297
Epoch 2: val_accuracy improved from 0.98047 to 0.98438, saving model to saved_models\weights-improvement.hdf5
16/16 [==============================] - 6s 373ms/step - loss: 0.2282 - accuracy: 0.9297 - val_loss: 0.0830 - val_accuracy: 0.9844
Epoch 3/30
16/16 [==============================] - ETA: 0s - loss: 0.2782 - accuracy: 0.9258
Epoch 3: val_accuracy did not improve from 0.98438
16/16 [==============================] - 6s 375ms/step - loss: 0.2782 - accuracy: 0.9258 - val_loss: 0.1152 - val_accuracy: 0.9805
Epoch 4/30
16/16 [==============================] - ETA: 0s - loss: 0.0777 - accuracy: 0.9801
Epoch 4: val_accuracy did not improve from 0.98438
16/16 [==============================] - 6s 354ms/step - loss: 0.0777 - accuracy: 0.9801 - val_loss: 0.0693 - val_accuracy: 0.9844
Epoch 5/30
16/16 [==============================] - ETA: 0s - loss: 0.0957 - accuracy: 0.9721
Epoch 5: val_accuracy did not improve from 0.98438
16/16 [==============================] - 6s 354ms/step - loss: 0.0957 - accuracy: 0.9721 - val_loss: 0.0919 - val_accuracy: 0.9766
Epoch 6/30
16/16 [==============================] - ETA: 0s - loss: 0.0564 - accuracy: 0.9922
Epoch 6: val_accuracy did not improve from 0.98438
16/16 [==============================] - 6s 372ms/step - loss: 0.0564 - accuracy: 0.9922 - val_loss: 0.0920 - val_accuracy: 0.9805
Epoch 6: early stopping
```

Fig. 12: Model Training

I. Saving Trained Model

```
[ ] model.save("pancreatic_tumor_model.h5")
    h = hs.history
    h.keys()

    dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

Fig. 13: Saving Trained Model

J. Plotting of Accuracy

```
plt.ylabel('accuracy')
plt.xlabel('epochs')
plt.plot(h["accuracy"])

[<matplotlib.lines.Line2D at 0x1b68b21bd50>]
```

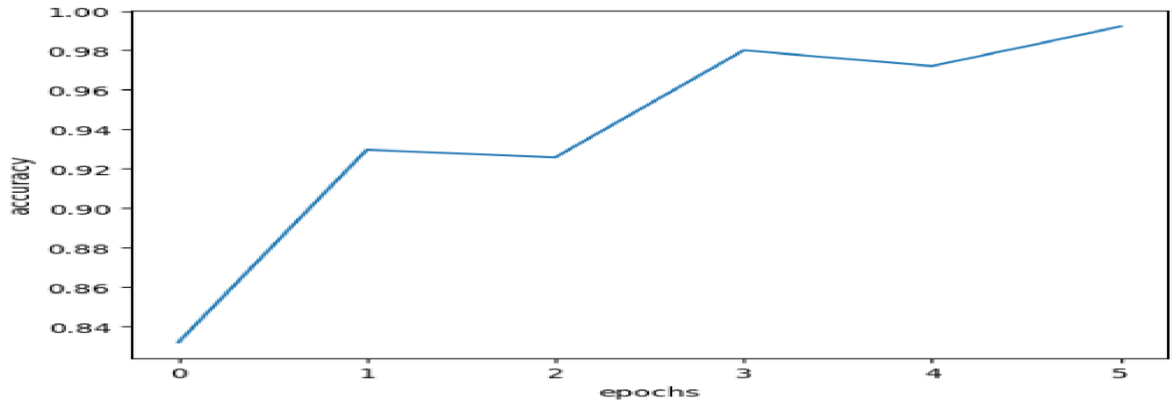


Fig. 14: Plotting of Accuracy

K. Plotting of Loss

```
plt.ylabel('loss')
plt.xlabel('epochs')
plt.plot(h["loss"])

[<matplotlib.lines.Line2D at 0x1b68b4453d0>]
```

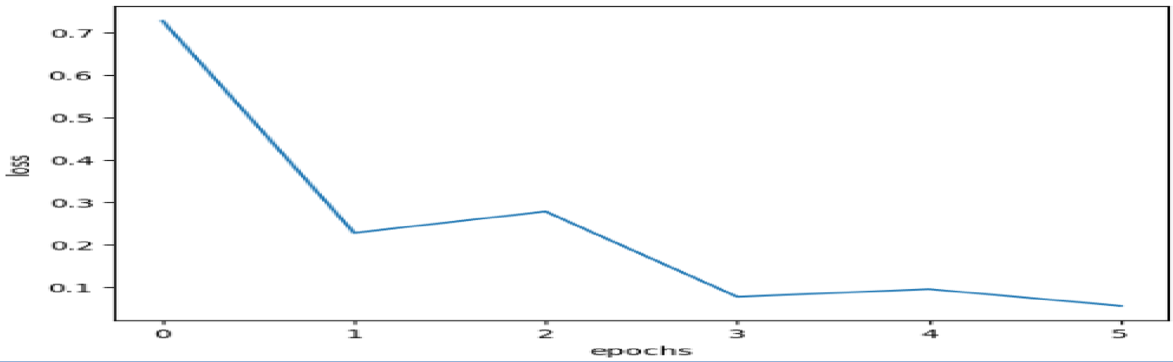


Fig. 15: Plotting of Loss

L. Testing and Test Augmentation

```
[ ] test_datagen = ImageDataGenerator(
        rescale=1./255,
        rotation_range=45,
        shear_range=0.2,
        zoom_range=0.2,
        horizontal_flip=True)

[ ] test_generator = test_datagen.flow_from_directory(
        '/content/Pancreatic_Tumor_Detection/test_train_split/test',
        target_size=(150, 150),
        batch_size=batch_size,
        class_mode='binary')

    Found 142 images belonging to 2 classes.
```

Fig. 16: Testing and Test Augmentation

M. Loading the saved Model

```
from keras.models import load_model
model=load_model("/content/Pancreatic_Tumor_Detection/saved_models/pancreatic_tumor_model.h5")

#Model Accuracy
acc=model.evaluate_generator(test_generator)[1]
print("Accuracy of our model is", acc)

C:\Users\dkvhe\AppData\Local\Temp\ipykernel_7928\1876032302.py:2: UserWarning: `Model.evaluate_generator` is deprecated and will be removed in a future version.
  acc=model.evaluate_generator(test_generator)[1]
Accuracy of our model is 0.98591548204422
```

Fig. 17: Loading the saved Model

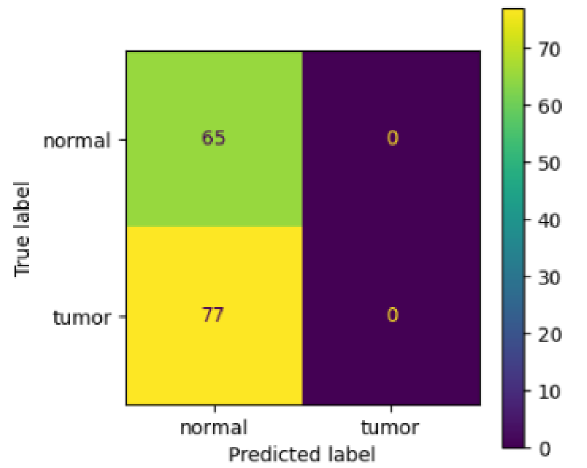
V. FINDINGS ON PANCREAS TUMORDETECTION

A. Confusion Matrix and Classification Report

A **confusion matrix** is a table that shows the performance of a classification model by comparing the actual and predicted labels of a dataset. It provides valuable insights into the model's accuracy, precision, recall, and F1-score for each class. On the other hand, a **classification report** is a summary of these metrics, providing a comprehensive evaluation of the model's performance across all classes. Both the confusion matrix and classification report help in understanding the effectiveness and limitations of a deep learning model for multi-class classification tasks.

```
[ ] Y_pred = model.predict_generator(test_generator)
    y_pred = np.argmax(Y_pred, axis=1)
    print('Confusion Matrix')
    # print(confusion_matrix(test_generator.classes, y_pred))

    target_names = ['normal', 'tumor']
    cm = confusion_matrix(test_generator.classes, y_pred)

    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=target_names)
    fig, ax = plt.subplots(figsize=(4,4))
    disp.plot(ax=ax)
    # disp.plot(cmap=plt.cm.Blues)
    plt.show()
    print('Classification Report')
    print(classification_report(test_generator.classes, y_pred, target_names=target_names))

    C:\Users\dkvhe\AppData\Local\Temp\ipykernel_7928\2358588086.py:1: UserWarning: `Model.predict_generator` is deprecated and will be removed in a future version.
      Y_pred = model.predict_generator(test_generator)
    Confusion Matrix
```

```
[ ] C:\Users\dkvhe\AppData\Local\Temp\ipykernel_7928\2358588086.py:1: UserWarning: `Model.predict_generator`
      Y_pred = model.predict_generator(test_generator)
    Confusion Matrix
```



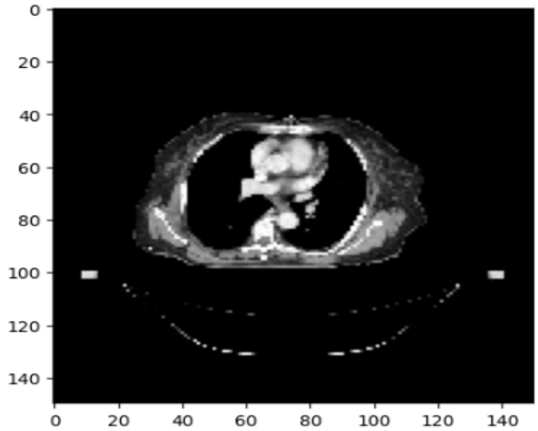

```
Classification Report
              precision    recall  f1-score   support

      normal       0.46      1.00      0.63        65
       tumor       0.00      0.00      0.00        77

    accuracy                           0.46       142
   macro avg       0.23      0.50      0.31       142
weighted avg       0.21      0.46      0.29       142
```

Fig. 18: Confusion Matrix and Classification Report

B. Loading and Testing a CT Scanned Image

```
[ ] path="/content/Pancreatic_Tumor_Detection/data_pan/data/pancreatic_tumor/1-003.jpg"
    img=load_img(path,target_size=(150,150))
    input_arr=img_to_array(img)/225
    plt.imshow(input_arr)
    plt.show()
    input_arr=np.expand_dims(input_arr,axis=0)
    pred=(model.predict(input_arr) > 0.5).astype("int32")
    if(pred==0):
      print("The image is normal")
    else:
      print("The image is having a Tumor")
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```




```
1/1 [==============================] - 0s 115ms/step
The image is having a Tumor
```

Fig. 19: Loading and Testing a CT Scanned Image

VI. SUMMARY OF FINDINGS

Deep learning has the potential to revolutionize pancreas tumor detection using CT images. By leveraging the power of artificial intelligence, deep learning models can be trained to identify pancreatic tumors more accurately and efficiently than traditional methods. This could lead to earlier detection of pancreatic cancer, which is important for improving patient outcomes.

VII. CONCLUSION OF THE STUDY

The evidence suggests that deep learning has the potential to significantly improve the early detection of pancreatic cancer. Deep learning-based systems can be used to analyze medical images to detect pancreatic tumors with high accuracy. This can lead to earlier diagnosis and treatment of pancreatic cancer, which could improve patient outcomes. Deep learning models have been shown to achieve high accuracy and sensitivity in detecting pancreatic tumors.

VIII. RECOMMENDATIONS

We strongly advocate the adoption of Deep Learning (DL) models based on CNN-enhanced algorithms to identify pancreatic tumor malignancy in light of our findings. It is the perfect answer for dealing with some hospitals and patients due to these potent properties. A lot of people die each year as a result of pancreatic cancer. It is feasible to diagnose pancreas tumors at an early stage thanks to the methods for finding and categorizing them.

Future research should focus on developing and validating deep learning-based systems for pancreas tumor detection in a clinical setting.

Deep learning-based systems should be integrated with existing clinical workflows to make them more accessible to clinicians and patients.

More research is needed to develop deep learning-based systems that can detect pancreatic tumors. This could lead to even more accurate and earlier detection of pancreatic cancer.

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