A
Project Report
On
Kidney Tumor Detection

(CE359 – Software Group Project-IV)

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Submitted to

Charotar University of Science & Technology (CHARUSAT)
for the Partial Fulfillment of the Requirements for the
Degree of Bachelor of Technology (B.Tech.)
in Computer Engineering (CE)
for 6th semester B.Tech.

Submitted at

Accredited with Grade A+ by NAAC

U & P U. PATEL DEPARTMENT OF COMPUTER ENGINEERING
(NBA Accredited)
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At: Changa, Dist: Anand, Pin: 388421.
April, 2022

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CERTIFICATE

This is to certify that the report entitled "**Kidney Tumor Detection**" is a bonafied work carried out by **Dhruv Puvar**(**20CE117), Nisarg Shah(20CE132), Shail Shah(20CE134)** under the guidance and supervision of **Dr. Ashwin Makwana** for the subject **Software Group Project (CE359)** of 6th Semester of Bachelor of Technology in **Computer Engineering** at Chandubhai S. Patel Institute of Technology (CSPIT), Faculty of Technology & Engineering (FTE) – CHARUSAT, Gujarat.

To the best of my knowledge and belief, this work embodies the work of candidate himself, has duly been completed, and fulfills the requirement of the ordinance relating to the B.Tech. Degree of the University and is up to the standard in respect of content, presentation and language for being referred by the examiner(s).

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DECLARATION BY THE CANDIDATES

We hereby declare that the project report entitled "**Kidney Tumor Detection**" submitted by us to Chandubhai S. Patel Institute of Technology, Changa in partial fulfilment of the requirements for the award of the degree of **B.Tech Computer Engineering**, from U & P U. Patel Department of Computer Engineering, CSPIT, FTE, is a record of bonafide CE359 Software Group Project carried out by us under the guidance of **Dr. Ashwin Makwana**. We further declare that the work carried out and documented in this project report has not been submitted anywhere else either in part or in full and it is the original work, for the award of any other degree or diploma in this institute or any other institute or university.

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This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

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Acknowledgment

We would like to express our gratitude to our primary supervisor, Dr. Ashwinkumar Makwana, who guided us throughout this project. This research behind it would not have been possible without the exceptional support of our team.

The zeal, knowledge, and meticulous attention to detail were an inspiration and helped us stay on track with our job. The generosity and expertise of each one of us have improved our study in countless ways and saved us from numerous mistakes; those that inevitably remain are solely our responsibility.

We appreciate all the people with whom we've had the pleasure of collaborating on this and other projects. Each member of our Research Team has provided considerable personal and professional guidance to one another, as well as teaching each other a great deal about scientific research and life in general.

Abstract

Kidney tumor detection is a crucial area of research in medical imaging, aimed at identifying and diagnosing tumors in the kidneys. This process involves the use of advanced imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound to obtain detailed images of the kidneys.

Recent advancements in medical imaging have led to the development of several automated techniques for detecting kidney tumors. These techniques utilize machine learning algorithms and deep learning neural networks to analyze the image data and accurately identify the presence of tumors.

The early detection of kidney tumors is essential in providing effective treatment and improving patient outcomes. Therefore, the development of accurate and efficient detection methods is of utmost importance.

This abstract summarizes the current state of research on kidney tumor detection, highlighting the various imaging techniques and automated methods used for identifying and diagnosing tumors in the kidneys.

CHAPTER 1: Introduction

1.1 Introduction:

The importance of early detection of kidney tumors (KT) to reduce the risk of further disease progression and preserve the patient's life. KT may not induce symptoms, but can be accidentally observed on radiography or cause subtle symptoms such as low hemoglobin, weakness, vomiting, and stomach pain. Anemia occurs in about 30 percent of KT patients. CT scans of the abdomen and pelvis are necessary tests to determine the presence of the tumor. The article emphasizes the need for accurate tumor diagnosis to choose the appropriate treatment method and improve the rate of recovery from the disease.

Deep learning approaches, including convolutional neural networks (CNNs), have shown great potential in detecting and classifying kidney tumors from medical imaging data such as computed tomography (CT) and magnetic resonance imaging (MRI). These methods rely on large amounts of training data to learn the relevant features and patterns associated with different types of kidney tumors.

In recent years, several studies have been conducted to explore the effectiveness of deep learning approaches in kidney tumor detection and classification. These studies have shown promising results, with high accuracy rates and faster processing times compared to traditional methods.

1.2 Research Definition

Kidney tumor detection and classification based on machine learning approaches is a field of research that involves the development and application of machine learning algorithms, specifically convolutional neural networks (CNNs), to analyze medical imaging data such as computed tomography (CT) and magnetic resonance imaging (MRI) to detect and classify kidney tumors. The goal of this research is to improve the accuracy and efficiency of kidney tumor detection and classification, leading to earlier detection, more accurate diagnosis, and more effective treatment options for patients. This research area also involves investigating the different types of deep learning and machine learning models and architectures that can be used, as well as the challenges and limitations associated with these approaches. Additionally, researchers in this field explore potential future directions for research, such as the integration of multiple imaging modalities and the use of explainable AI techniques to improve the interpretability of the models.

1.3 Problem Description

The detection of kidney tumors is a critical step in the diagnosis and treatment of renal cancer. Early detection of kidney tumors is crucial for improving patient outcomes and increasing the success rate of treatment. However, the process of detecting kidney tumors can be challenging and complex, and there is a need to find the best algorithm for accurately detecting and classifying kidney tumors.

One of the main challenges in detecting kidney tumors is the lack of clear symptoms in the early stages of the disease. Many kidney tumors are discovered incidentally during imaging scans for other conditions. Therefore, imaging tests such as CT scans, MRI, and ultrasound are the primary means of detecting kidney tumors.

Traditional methods of detecting kidney tumors involve manual interpretation of medical images by radiologists, which can be time-consuming, subjective, and prone to errors. This highlights the need for automated algorithms that can analyze medical images and accurately detect kidney tumors.

Deep learning approaches, specifically CNNs, have shown great potential in accurately detecting and classifying kidney tumors from medical images. However, there are still challenges in developing and selecting the best algorithm for kidney tumor detection, such as the need for large amounts of high-quality training data, variability in tumor characteristics, and the need for explainable and interpretable AI models.

Therefore, the problem at hand is to find the best algorithm for detecting kidney tumors accurately and efficiently, taking into account the specific challenges and limitations of the available data and resources. The goal is to develop an automated system that can aid in the early detection and accurate diagnosis of kidney tumors, leading to improved patient outcomes and better overall health outcomes.

1.4 Motivation

The motivation for conducting research in kidney tumor detection and classification based on machine learning approaches is multifaceted. Firstly, deep learning techniques have shown great promise in achieving high accuracy in detecting and classifying kidney tumors, which could lead to earlier detection and improved treatment outcomes for patients. Secondly, traditional methods of detecting kidney tumors can be time-consuming and subjective, whereas deep learning algorithms can automate the process, providing a more efficient means of detection**.**

Furthermore, the field of deep learning is rapidly evolving, and there is potential for further development and improvement in kidney tumor detection and classification using these techniques. Overall, research in kidney tumor detection and classification based on deep learning approaches has the potential to contribute to the development of more advanced AI techniques for medical imaging analysis, with potential applications beyond kidney tumor detection.

1.5 Scope:

The scope of kidney tumor detection includes the development and implementation of various techniques and approaches for accurate and early detection of kidney tumors. This may involve the use of medical imaging technologies such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound to capture images of the kidneys and identify potential tumor growth. In recent years, the use of deep learning algorithms and machine learning has become increasingly popular for kidney tumor detection, allowing for more efficient and accurate diagnosis.

Objective:

The objective of kidney tumor detection is to accurately identify and diagnose the presence of tumors in the kidneys as early as possible. Early detection is critical for successful treatment and management of kidney tumors, as it allows for timely intervention to prevent the progression of the disease and reduce the risk of complications.

The goal of kidney tumor detection is to improve patient outcomes and quality of life by providing accurate and timely diagnoses, allowing for personalized treatment plans, and reducing the burden of disease on patients and healthcare systems. Additionally, by promoting awareness and early detection of kidney tumors, the objective of kidney tumor detection is to prevent or reduce the incidence of the disease and improve overall public health.

1.6 Planning

- literature review
    i. researched about previously applied approaches
    ii. different other approaches
- Dataset Creation
    i. To collect various kidney tumor images from various research paper
    ii. It could be images or biomarkers
- Creating model or training pre-defined model
- Testing the accuracy and other parameters

CHAPTER 2: Literature Review & Comparative study

2.1 Review Previous Research Findings

Link of paper: -

https://www.mdpi.com/2073-8994/12/1/154

Classification of Kidney Cancer Data Using Cost-Sensitive Hybrid Deep Learning Approach

Summary: -

This study used bioinformatics approaches to identify genes that are useful for the diagnosis and prognosis of patients with cancer. Deep learning methods have been used to accurately predict the disease condition of patients, and lifestyle factors such as poor diet, physical inactivity, smoking, and alcohol consumption are associated with an increased risk of kidney cancer. Machine learning and data mining techniques have been successfully used to analyze image data from patients with breast cancer, and pathologist-based diagnosis has been used to predict the degree of risk of 20 cancers. Deep learning approaches have been applied to the research of cancer using gene expression data. This study combined gene expression and clinical data from patients with kidney cancer from TCGA and applied our proposed deep learning, end-to-end COST-HDL approach. The objectives of this study were to extract deep features from gene biomarkers for precisely predicting prognosis, overcome differences in various types of cancer data, and develop an end- to-end prediction model by comparing and analyzing classification algorithms using the extracted genes.

Systematic Literature Review on Application of Artificial Intelligence in Cancer Detection Using Image Processing

Summary: -

Cancer are always posing low survival rate which result in need of more effective algorithm using AI to detect cancer and treat it. Subclasses of machine learning and deep learning which are use to work with large amount of data are use to implement this. In this research they have implemented Systematic literature review which showcases the most effective algorithm as Catboost (AUC 0.939) and Support vector Machine (SVM) (AUC 0.934)

This research flows Systematic literature Review over all the corelated research carried to detect cancer, like Deep Learning Neural Network, Convolutional Neural Network, CatBoost, Support vector Machine(SVM) etc. It Revolves around 2 research questions and finding answer to it. On the basis of AUC(Area under the Curve) the methods were analysed.

Kidney Tumor Segmentation and Detection on Computed Tomography Data

Summary: -

Using imaging techniques helps renal tumor. Major task is to segment the CT images into 3 parts kidney ,tumor and vascular tree, to provide better visualization and anatomical structure prior to surgical intervention. First step in this approach is to applying image segmentation based on thresholding, region growing or feature extractions. Then more advanced algorithms Atlas segmentation or Active Shape/Appearance model. Last group with level set techniques. Second steps involve classification of kidney region. Classification based on kidney, tumor and vascular tree using RUSBoost with decision tree.

Link of paper: -

https://ieeexplore.ieee.org/document/9115017

Dual Kidney-Inspired Algorithm for Water Quality Prediction and Cancer Detection

Summary:

Cooperation between the kidneys in the human body results in a perfect blood filtration process if both kidneys are healthy [34]. In the biological system of kidneys in human body, checking the Glomerular Filtration Rate (GFR) is the best investigation to calculate the level of kidney function and, as a result, decide the stage of kidney disease. If GFR is greater than 60 in GFR medical test in the biological system of kidneys, the kidney function is normal. When one kidney gets damaged and the GFR reported in kidneys functionality test results is between 15 and 60, some medication and treatment is usually required. However, a significant problem arises when the GFR in kidneys functionality test is less than 15 as this denotes that one or both kidneys is failing to perform the filtration process. If one of the kidneys fails, the other kidney filters all the blood. If both kidneys fail, then dialysis or transplant is applied as a treatment. Dual-KA is a simulation of this cooperation between two kidneys. In Dual-KA, the GFR is checked in each iteration, each population.

Dataset: -

Table 5. Effect of loss function of the COST-HDL approach. The best results are shown in bold.

Prognosis	Loss	Accuracy	Precision	Recall	F1-Score
Sample Type	MSE	89.13	44.57	50.00	47.13
	Focal	99.57	99.76	98.00	98.86
	Total	**100.00**	**100.00**	**100.00**	**100.00**
Primary Diagnosis	MSE	62.93	43.86	47.89	42.63
	Focal	96.55	97.13	95.01	95.97
	Total	**96.98**	**97.43**	**95.68**	**96.49**
Tumor Stage	MSE	12.05	7.92	26.32	7.31
	Focal	54.46	45.15	45.05	43.76
	Total	**56.70**	**49.41**	**46.14**	**46.68**
Vital Status	MSE	73.71	36.85	50.00	42.43
	Focal	76.29	69.00	67.05	67.83
	Total	**76.72**	**69.78**	**68.92**	**69.32**

Different Links

MRI/CT SCAN images and CSVs: -

https://www.kaggle.com/datasets/atreyamajumdar/kidney-cancer

https://www.kaggle.com/datasets/nazmul0087/ct-kidney-dataset-normal-cyst-tumor-and-stone

https://www.kaggle.com/datasets/obulisainaren/multi-cancer

Method: -

COST-HDL approach → Results

Table 5. Effect of loss function of the COST-HDL approach. The best results are shown in bold.

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Description: -

They collected TCGA data from 1157 patients with kidney cancer and other clinical information including sample type, primary diagnosis, tumor stage, and vital status.

The kidney cancer dataset was used to extract the complex structure of gene biomarkers and estimate classification accuracy as risk factors by sample type, primary diagnosis, tumor stage, and vital status representing the state of patients.

The proposed COST-HDL approach which inputs the gene expression data of kidney cancer from the TCGA portal and outputs four kinds of prognoses namely, sample type, primary diagnosis, tumor stage, and vital status.

Therefore, in this study, we used the 5-layer DAE model (the first 2 layers for encoding, the middle layer for gene extraction, and the last 2 layers for decoding) to extract significant genes and extract deep features from gene biomarkers as a result.

2.2 Comparative Study

The accuracy of a Sequential Convolutional Neural Network (CNN) model in detecting kidney tumors can also vary depending on several factors such as the quality and quantity of data used for training and testing the model, the architecture and hyperparameters of the CNN model, and the evaluation metrics used.

VGG NET model provides us accuracy of 100% after 5 epochs.

Several studies have reported promising results using SVM algorithms for kidney tumor detection. Our model accuracy is 99% using SVM with a radial basis function kernel for classifying kidney tumors on computed tomography (CT) images.

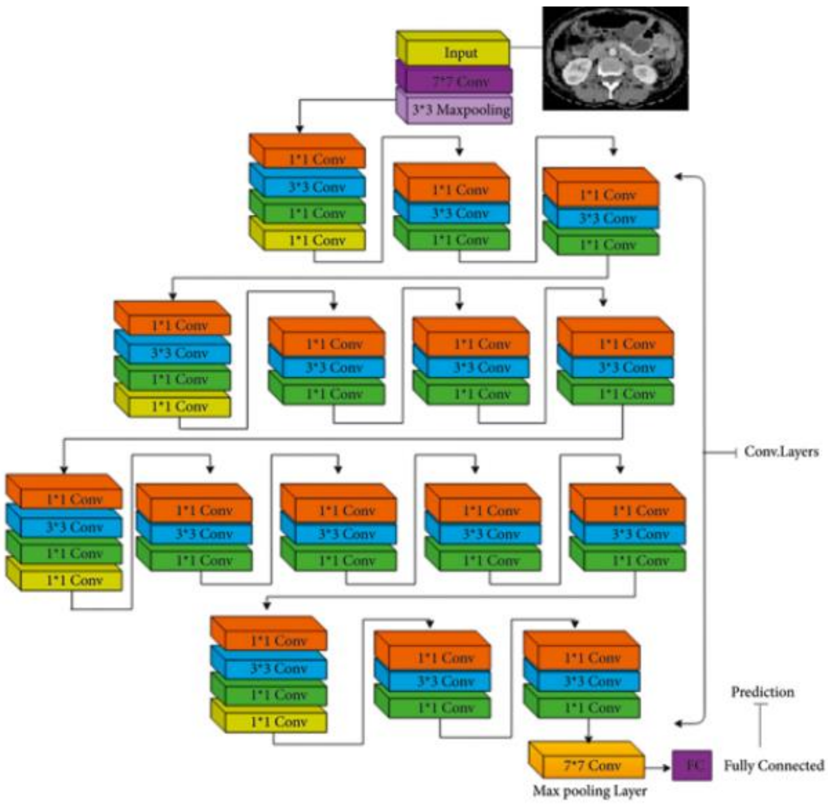
Performance matrix:

Model Name	Accuracy	Precision	Recall	F1 Score
CNN	0.998	0.994	1.00	0.99
VGG Net	0.98	1.0	0.998	0.999
SVM	0.987	0.992	0.968	0.980

CHAPTER 3 : Proposed Model

3.1 Model

CNN Model



The provided code creates a Convolutional Neural Network (CNN) model using the Keras API. The model consists of three convolutional layers, followed by a flattening layer, two fully connected layers, and an output layer with a sigmoid activation function.

The input to the model is a 3-channel image with a shape of (256, 256, 3). The first convolutional layer has 32 filters with a kernel size of (3, 3), followed by a max pooling layer with a pool size of (2, 2) and stride of 2. The second convolutional layer has 64 filters with a kernel size of (3, 3), followed by another max pooling layer with the same configuration. The third convolutional layer has 128 filters with a kernel size of (3, 3), followed by the last max pooling layer with the same configuration.

After the convolutional layers, the output is flattened and passed to two fully connected layers with 128 and 64 units, respectively, and a ReLU activation function. Finally, an output layer with a sigmoid activation function is added to output the predicted class probabilities.

The model is compiled with binary cross-entropy as the loss function and the Adam optimizer. During training, the accuracy and loss of the model are monitored for both the training and validation sets. The model is trained for 10 epochs.

VGG Net

VGG net. It is using the Keras Sequential model API to build the model, which has multiple layers of convolution and pooling, followed by some dense layers with dropout regularization. The purpose of this model is to classify images into two categories using a sigmoid activation function.

The layers in the model are as follows:

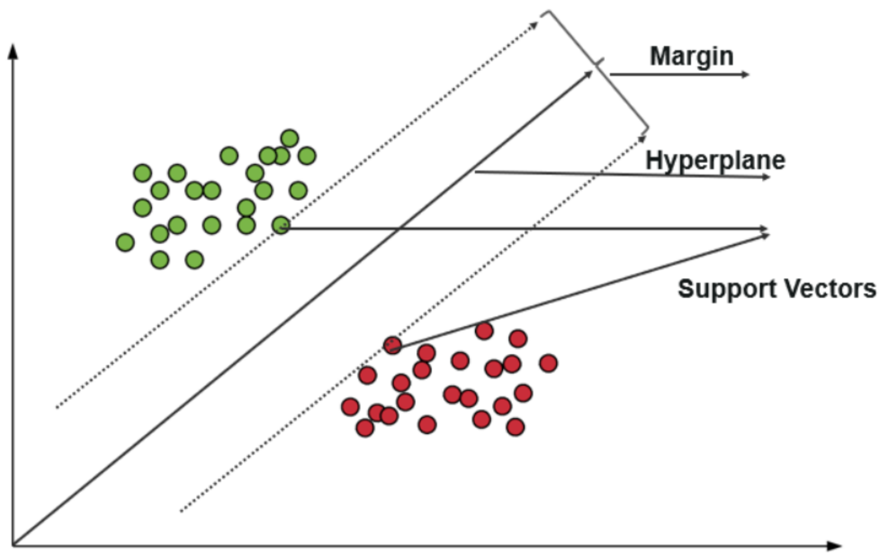
ZeroPadding2D layer to preserve spatial resolution, Convolution2D layer with 64 filters of size 3x3, MaxPooling 2D layer with a pool size of 2x2 and stride of 2.2, two more sets of convolution2D and MaxPooling2D layers, each with 128 filters.

A Flatten layer to convert the 2D output from the previous layer into a 1D vector, two Dense layers with 128 and 64 units respectively, followed by ReLU activation function and Dropout regularization, and a final Dense layer with 1 unit and a sigmoidal activation function to classify the images.

SVM(Support Vector Machine)

SVM (Support Vector Machine) is an Supervised Learning Algorithm which is well known for its use in classification and Regression Problems. However mainly used in Classification Problems in Machine Learning.

SVM Model segregates the elements/objects into over a multi-dimensional space where each co-ordinates represent features. It uses a hyperplane (line in 2-D space) to segregate objects.



Flow of execution of the model

1. Extract Data(Images) into Normal and Tumour named Folders respectively
2. Initialize two list X and Y for storing all images and their labels respectively
3. Covert the regular list into NumPy array
4. Convert 3-Dimensional list X into 2-Dimensional.
5. Splitting the overall data into Train and testing set, respectively.
6. Reinitialize the intensity values in the images from 0-255 to 0-1 (Binary)
7. Creating Support Vector Classifier using SVC library
8. Fitting the Classifier using train datasets
9. Predicting Performance metrics for the test dataset

CHAPTER 4: Conclusion

Conclusion:

The code provided creates a Convolutional Neural Network (CNN) model using Keras, with three convolutional layers, each followed by max pooling layers, and three fully connected (Dense) layers. The model is compiled with binary cross-entropy loss and Adam optimizer, and trained on a dataset of images belonging to two classes (presumably binary classification problem), achieving high accuracy on both the training and validation sets. The accuracy of VGG-Net is 98% after 5 epochs and for CNN model is 99.8%. The accuracy of SVM model is 98.7%.

CHAPTER 5: Future idea

Future Proposed idea:

By using a VGG Net and SVM model as the basis for a GUI, it may be possible to develop a more intuitive and interactive interface for tasks that involve visual data, such as kidney tumor detection. The CNN-based GUI could potentially allow users to input visual data and receive output in real-time, making it a powerful tool for detection of kidney tumor.

References

https://www.hindawi.com/journals/jhe/2022/3861161/

https://github.com/DaliaAlzubi/Kidney_Tumor_Detection_And_Classification