## **PELVIC URETERO JUNCTION OBSTRUCTION DETECTION USING DEEP LEARNING**

## A PROJECT REPORT

*Submitted by*

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*Under the Guidance of*

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*in partial fulfillment of the requirements for the degree of*

**BACHELOR OF TECHNOLOGY**

# in

**COMPUTER SCIENCE AND ENGINEERING**



**DEPARTMENT OF COMPUTING TECHNOLOGIES**

# COLLEGE OF ENGINEERING AND TECHNOLOGY

# SRM INSTITUTE OF SCIENCE AND TECHNOLOGY KATTANKULATHUR– 603 203

**MARCH 2024**



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iii**ACKNOWLEDGEMENT**

We express our humble gratitude to **Dr. C. Muthamizhchelvan**, Vice-Chancellor, SRM Institute of Science and Technology, for the facilities extended for the project work and his continued support.

We extend our sincere thanks to Dean-CET, SRM Institute of Science and Technology, **Dr. T. V. Gopal**, for his invaluable support.

We wish to thank **Dr. Revathi Venkataraman**, Professor and Chairperson, School of Computing, SRM Institute of Science and Technology, for her support throughout the project work.

We are incredibly grateful to our Head of the Department, **Dr. M. Pushpalatha,** Professor, Department of Computing Technologies, SRM Institute of Science and Technology, for her suggestions and encouragement at all the stages of the project work.

We want to convey our thanks to our Project Coordinators, **Dr.S.Nithiya, Dr. N. Nithiyanadam, Dr. D. Malathi and Dr. K.R.Jhansi,** Panel Head and **Mrs. Divya Mohan**, Assistant Professor and Panel Members Department of Computing Technologies, SRM Institute of Science and Technology, for their inputs during the project reviews and support.

We register our immeasurable thanks to our Faculty Advisor, **Dr. T. K. Sivakumar**, Assistant Professor, Department of Computing Technologies, SRM Institute of Science and Technology, for leading and helping us to complete our course.

Our inexpressible respect and thanks to our guide, **Mrs. Divya Mohan**, Assistant Professor,

Department of Computing Technologies, SRM Institute of Science and Technology, for providing us with an opportunity to pursue our project under her mentorship. She provided us with the

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freedom and support to explore the research topics of our interest. Her passion for solving problems and making a difference in the world has always been inspiring.

We sincerely thank all the staff and students of Computing Technologies Department, School of Computing, S.R.M Institute of Science and Technology, for their help during our project. Finally, we would like to thank our parents, family members, and friends for their unconditional love, constant support and encouragement.

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**ABSTRACT**

# This This research endeavors to introduce a pioneering deep learning pipeline tailored specifically for precise medical image classification, with a primary focus on distinguishing between "PUJ obstruction" and "Normal" conditions. The methodology involves leveraging transfer learning from well-established pre-trained CNN models like VGG16, InceptionV3, and DenseNet121. Through this approach, the framework aims to optimize feature extraction, thereby enhancing the accuracy of classification. To further bolster model performance, custom convolutional layers are integrated, which are tailored to the specific requirements of medical image analysis. Rigorous evaluation of the developed pipeline is conducted on meticulously labeled datasets, employing key metrics such as accuracy and F1-score. These metrics serve as robust indicators of the model's efficacy in accurately categorizing medical images. In addition to quantitative assessments, advanced visualization techniques are employed to provide deeper insights into the model's decision-making process. Techniques such as t-SNE are utilized for visualizing feature embeddings, enabling a comprehensive understanding of the underlying data manifold. Moreover, activation maps are generated to facilitate the interpretation of learned representations, shedding light on the regions of interest within the medical images that contribute significantly to the classification outcomes. This comprehensive approach marks a significant advancement in the field of medical image analysis. By combining state-of-the-art deep learning techniques with advanced visualization methods, the proposed pipeline holds the potential to significantly elevate diagnostic precision. Ultimately, this could lead to tangible

# Keywords: Pelvic Uretero Junction (PUJ), VGG16, InceptionV3, and DenseNet121, Urological Condition, Mobile NetV2, t-SNE Visualization, Confusion Matrix and Activation Map.

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**LIST OF SYMBOLS AND ABBREVIATIONS**

**PUJ** Pelvic Uretero Junction

**CNN** Convolutional Neural Network

**RNN** Recurrent Neural Network

**VGG16** Visual Geometry Group

**t−SNE** t-Distributed Stochastic Neighbor Embedding

**AI** Artificial Intelligence

**ML** Deep Learning

**DL** Deep Learning

**MRI** Magnetic Resonance Imaging

**CT** Computed Tomography

**MRU** Magnetic Resonance Urography

**F1** F1 Score (a measure of a test's accuracy)

**ROI** Region of Interest

**CAD** Computer-Aided Diagnosis

**API** Application Programming Interface

**GUI** Graphical User Interface

**CSV** Comma-Separated Values

**TP** True Positives

**TN** True Negatives

**FP** False Positives

**FN** False Negatives

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**CHAPTER 1**

**INTRODUCTION**

**1.1 General**

Pelvic Uretero Junction Obstruction (PUJO) is a condition with profound implications for patient health and healthcare systems. The deployment of Deep Learning in PUJO detection is highly significant due to its capacity for early intervention, enhancing diagnostic accuracy, reducing healthcare costs, improving patient care, enabling telemedicine possibilities, providing data-driven insights, driving research advancements, tailoring treatment plans, enhancing efficiency, and fostering interdisciplinary collaboration. This application of Deep Learning represents a pivotal step forward in urology and medical imaging, promising to impact healthcare and research significantly. In this report, we delve into the methodology and results of our efforts to leverage Deep Learning for PUJO detection.

The project's evaluation involves assessing the model's performance through key metrics, including accuracy and the F1-score. By effectively classifying PUJ obstruction, this Deep Learning approach offers a valuable tool for medical professionals, providing a foundation for early diagnosis and treatment planning. Additionally, the project incorporates t-Distributed Stochastic Neighbor Embedding (t-SNE) for data visualization, aiding in the interpretation of feature separation. This visual representation enhances our understanding of the model's ability to distinguish between PUJ obstruction and normal cases, making it an essential resource for professionals and researchers in the field of urology and medical imaging.

**1.2 Prevalence of Urological Disorders:**

Urological disorders encompass a broad spectrum of conditions affecting the urinary tract and male reproductive system. These disorders pose a significant health challenge, with a prevalence that extends across geographic boundaries and demographic groups. According to global health data, urological disorders, including Pelvic Uretero Junction Obstruction (PUJO), are not uncommon.

The worldwide prevalence of such disorders underscores the urgency of robust and accurate diagnostic tools. In the context of PUJO, the condition's incidence varies but can affect individuals at any age, from infants to adults. While some cases manifest symptoms early in life, others remain asymptomatic for extended periods, making timely detection and intervention crucial.

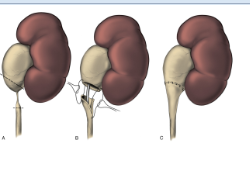


Fig 1.2 Different Stages of PUJ Surgery

Urological disorders extend beyond PUJ obstruction and encompass a wide spectrum of conditions that impact the urinary system. These conditions range from urinary tract infections (UTIs) and kidney stones to benign prostatic hyperplasia (BPH), urinary incontinence, and various urological cancers such as bladder cancer and prostate cancer. The prevalence of these disorders varies greatly and can be influenced by multiple factors. For example, UTIs are relatively common, particularly among women, while the likelihood of developing prostate cancer rises with age.

Understanding the prevalence of urological disorders is crucial for healthcare providers, researchers, and policymakers. It allows for the development of effective strategies for diagnosis, treatment, and prevention. Furthermore, the prevalence of these disorders is influenced by factors such as genetics, lifestyle, and access to healthcare. Reliable epidemiological data plays a pivotal role in characterizing the occurrence of these conditions in specific populations and regions, aiding in the allocation of healthcare resources and the enhancement of patient care.

The project "Pelvic Uretero Junction Obstruction Detection using Deep Learning" holds promise in contributing to the management of urological disorders, particularly PUJ obstruction. By offering a Deep Learning-based tool for early detection and diagnosis, the project addresses the critical need for timely intervention, potentially improving patient outcomes and enhancing the understanding of the prevalence and patterns of PUJ obstruction and other urological conditions.

**1.3 The Role of Medical Imaging:**

Medical imaging stands as a cornerstone of contemporary healthcare, providing non-invasive windows into the human body. In the context of urology, it serves as an indispensable tool, facilitating early detection and accurate diagnosis. Medical imaging techniques allow clinicians to visualize the urinary system, detect anomalies, precisely localize issues, monitor disease progression, and support minimally invasive procedures. Furthermore, it aids in preoperative planning, screening, and early detection. In our project, the integration of medical imaging with Deep Learning is poised to redefine the diagnosis and management of Pelvic Uretero Junction Obstruction (PUJO), promising not only enhanced diagnostic accuracy but also the optimization of patient care and clinical outcomes in the field of urology.

In the context of the project, medical imaging serves as the primary data source for training and testing the Deep Learning model. The images of the urinary tract, acquired through different imaging techniques, are the foundation of the model's learning process. Feature extraction, a critical step in preparing the data for Deep Learning, uncovers meaningful patterns and structures within the images relevant to PUJ obstruction diagnosis.

The extracted features from medical images become the basis for training a Support Vector Machine (SVM) classifier. The Deep Learning model learns to classify images into two categories: PUJ obstruction and normal cases, leveraging information from the medical imaging data. The validation and evaluation of the model rely on this imaging data, where the model's predictions are compared against ground truth labels from the medical images. This evaluation process provides insights into the model's accuracy and diagnostic capabilities, contributing to its refinement and reliability.

Furthermore, medical imaging data is visualized and interpreted using t-Distributed Stochastic Neighbor Embedding (t-SNE), which offers a lower-dimensional representation of the features. This visualization aids researchers and healthcare professionals in understanding feature separation and clustering, facilitating the exploration of patterns and relationships within the medical imaging data. In summary, medical imaging is the cornerstone of the project, driving accurate diagnosis, model training, and evaluation, while paving the way for improved PUJ obstruction detection and patient care.

**1.4 Computer Vision:**

In the realm of medical imaging, computer vision, a subfield of artificial intelligence, has emerged as a transformative force. Computer vision technologies, driven by advanced algorithms and deep learning models, empower healthcare professionals to extract valuable insights from medical images. These technologies play a pivotal role in the accurate interpretation of complex visual data, making them indispensable in fields like radiology and diagnostic medicine. In the context of our project, which focuses on the detection of Pelvic Uretero Junction Obstruction (PUJO), computer vision finds its relevance through the analysis and interpretation of medical images. By harnessing the capabilities of computer vision and Deep Learning, we aim to not only enhance the precision of PUJO diagnosis but also contribute to the broader evolution of medical imaging and its applications in urology. This integration of computer vision and medical imaging exemplifies the intersection of cutting-edge technology with critical healthcare challenges, promising a more accurate and efficient path to diagnosing PUJO.

**1.5 Computer Vision in Healthcare:**

Within the domain of healthcare, computer vision has emerged as a catalyst for transformative change. Its profound impact is most vividly witnessed in the field of medical imaging, where it plays a pivotal role in enhancing diagnostic accuracy, expediting treatment, and reshaping the patient care landscape.

**1.5.1 Enhanced Diagnostic Precision:**

Computer vision systems, underpinned by sophisticated algorithms and deep learning models, have redefined the interpretation of medical images. Radiologists and diagnosticians can now rely on intelligent systems that excel in identifying subtle abnormalities and intricate patterns within X-rays, MRIs, CT scans, and other forms of medical imaging. This precision is paramount in the early detection and accurate diagnosis of conditions, from tumors and fractures to vascular anomalies.

**1.5.2 Accelerated Treatment:**

In the context of medical imaging, computer vision expedites the entire healthcare journey. It not only aids in swift diagnosis but also streamlines treatment planning. Surgeons, for instance, benefit from 3D reconstructions generated from 2D images, facilitating preoperative planning and intraoperative navigation.

**1.5.3 Telemedicine and Remote Consultation:**

Computer vision is the linchpin of telemedicine, bridging geographical distances and facilitating remote consultations. Patients in remote or underserved areas can receive expert medical opinions by sharing medical images and records, all interpreted and analyzed by computer vision systems.

**1.5.4 Radiomics and Data-Driven Insights:**

The marriage of computer vision with radiomics, the study of medical images and their quantitative features, unleashes a wealth of data-driven insights. Beyond diagnosis, this synergy supports research efforts by offering valuable information for disease characterization, treatment response assessment, and prognosis.

**1.5.5 Workflow Optimization:**

The efficiency gains offered by computer vision systems are not confined to diagnostic accuracy alone. They extend to the entire healthcare workflow, from automating image analysis to streamlining the management of patient records, thereby reducing the administrative burden on healthcare providers.

**1.5.6 Point-of-Care Diagnostics**:

In addition to traditional medical imaging, computer vision extends its reach to point-of-care diagnostics. Portable devices equipped with computer vision algorithms empower healthcare professionals to make rapid assessments and decisions at the patient's bedside, from diagnosing skin conditions to measuring vital signs.

**1.5.7 Precision Medicine:**

Computer vision systems contribute to the realization of precision medicine by tailoring treatments to individual patients. By leveraging patient-specific data extracted from medical images, healthcare providers can fine-tune therapeutic interventions.

**1.5.8 Ethical Considerations:**

With great transformative power comes great responsibility. The ethical dimensions of computer vision in healthcare, including patient privacy, data security, and bias mitigation, are crucial to ensuring its responsible and equitable use.

**1.6 Convolutional neural Network (VGG16):**

In the realm of modern healthcare, where technology and precision intertwine, Convolutional Neural Networks (CNNs) emerge as a formidable force, revolutionizing the interpretation of visual data and advancing diagnostic capabilities. In particular, the integration of advanced CNN architectures like VGG16 has the potential to reshape the landscape of medical imaging, enhancing the accuracy and efficiency of diagnostic processes.

CNNs, designed to mimic the human visual system, are neural networks tailored for tasks involving visual data, making them particularly adept at image analysis. These networks rely on convolutional layers to extract intricate features from images, such as edges, textures, shapes, and complex patterns. Within the realm of healthcare, where radiological and medical images are central to diagnostics, the ability of CNNs to discern these subtle nuances carries profound significance.

VGG16, a distinguished variant of CNNs, introduces an element of efficiency that is pivotal in the context of healthcare. Renowned for its speed and computational thriftiness, VGG16 is an architecture tailored for mobile and embedded applications. Its role in this project extends beyond mere algorithmic capabilities; it bridges the chasm between traditional medical imaging and the vanguard of Deep Learning.

VGG16 serves as the feature extractor in the project, a function that underpins the accurate detection of Pelvic Uretero Junction Obstruction (PUJO). As it processes each medical image, it dissects the visual cues that define the condition, enabling the subsequent classification of images as indicative of PUJO or normal. This introduction of VGG16 into the realm of medical imaging epitomizes a paradigm shift in diagnostics. It catapults precision and automation into the forefront, heralding more robust and reliable diagnostic tools, which are indispensable in the early detection and intervention of conditions such as PUJO.

As we venture deeper into the intricate layers of VGG16 and their impact on healthcare, the full scope of its potential comes to light. Each convolutional layer represents a step forward in the quest for more precise and efficient healthcare, capable of transforming the diagnostic landscape. In our exploration of the profound ways in which VGG16, as a representative of CNNs, is reshaping the realm of medical imaging, we uncover a vision of enhanced diagnosis and treatment for urological conditions, paving the way for a future where technology and healthcare seamlessly converge for the betterment of patient care.

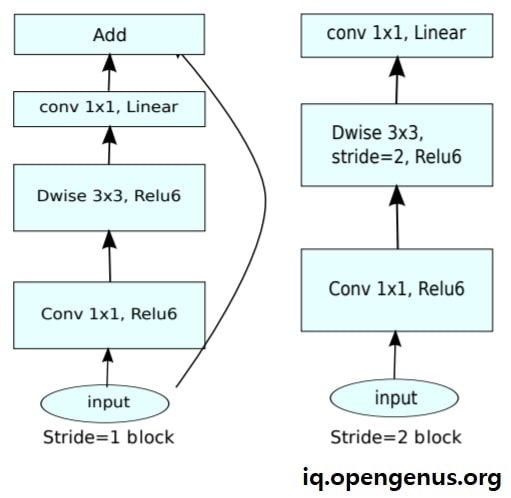


Fig 1.6 VGG16 Architecture

**1.7 InceptionV3:**

In the dynamic realm of modern healthcare, where technology and precision intertwine to redefine diagnostic standards, InceptionV3 emerges as a transformative force, elevating the interpretation of visual data to unprecedented levels of accuracy and efficiency. In the context of medical imaging, the integration of sophisticated CNN architectures like InceptionV3 holds immense promise, reshaping the landscape of diagnostics and offering new avenues for enhanced patient care.

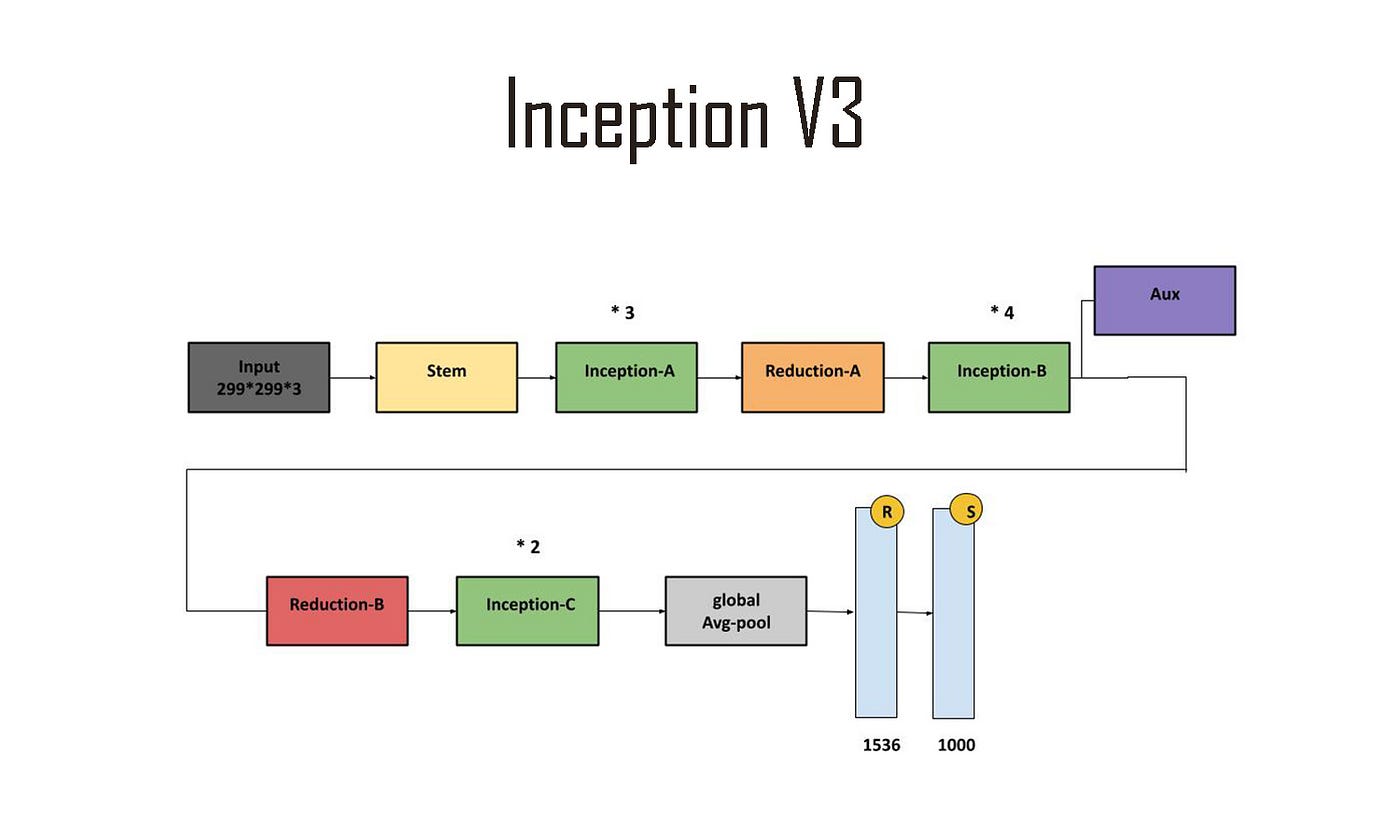


Fig 1.7 InceptionV3 Architecture

Convolutional Neural Networks (CNNs) stand as the backbone of this technological revolution, intricately designed to emulate the complexities of the human visual system. InceptionV3, a notable variant of CNNs, represents a pinnacle of innovation, renowned for its ability to extract rich features from images with remarkable precision and speed. Within the healthcare domain, where precise analysis of radiological and medical images is paramount, InceptionV3's prowess in discerning subtle nuances holds immense potential for transforming diagnostic practices.

At the heart of InceptionV3 lies a network of convolutional layers meticulously engineered to unravel the intricate details embedded within medical images. These layers operate in tandem, systematically extracting nuanced features such as textures, shapes, and intricate patterns, thereby enabling the network to decipher the visual cues indicative of various medical conditions. In the context of this project, InceptionV3 assumes the role of a powerful feature extractor, poised to accurately detect Pelvic Uretero Junction Obstruction (PUJO) and differentiate it from normal conditions.

The integration of InceptionV3 into the realm of medical imaging signifies a paradigm shift in diagnostic methodologies, ushering in an era of heightened precision and efficiency. As it delves into each medical image, InceptionV3 meticulously dissects the visual elements that define PUJO, facilitating precise classification and enabling timely interventions. This fusion of cutting-edge technology with healthcare not only streamlines diagnostic processes but also underscores the potential for early detection and intervention, particularly in the context of urological conditions.

As we delve deeper into the intricate layers of InceptionV3 and unravel its profound impact on healthcare, we unveil a vision of enhanced diagnostic capabilities and improved patient outcomes. Each convolutional layer within InceptionV3 represents a stride forward in the pursuit of more accurate and efficient healthcare solutions, offering a glimpse into a future where technology serves as a catalyst for better patient care and medical innovation.

**1.7.1 InceptionV3 Modal Architecture:**

The InceptionV3 architecture is a deep convolutional neural network (CNN) designed for various computer vision tasks, including image classification and object detection. It was developed by Google Research and represents an evolution of the original Inception architecture.

Here's a breakdown of the key components and concepts within the InceptionV3 architecture:

Inception Modules: The hallmark of the Inception architecture is its use of "Inception modules," which are designed to capture different scales of information within the same layer. These modules consist of multiple parallel convolutional branches with different kernel sizes (1x1, 3x3, 5x5), pooling operations, and sometimes even dimensionality reduction techniques like 1x1 convolutions. By combining these different operations, the network can effectively capture both local and global features within the same layer.

Factorization: InceptionV3 utilizes factorized convolutions to reduce computational complexity while maintaining model performance. Instead of using a single large kernel size, factorized convolutions break down the convolution operation into smaller convolutions, reducing the number of parameters and computational cost.

Stem: The initial layers of the network, often referred to as the "stem," perform basic feature extraction and preprocessing operations on the input images. In InceptionV3, this typically involves a series of convolutional and pooling layers to extract low-level features.

Auxiliary Classifiers: InceptionV3 includes auxiliary classifiers at intermediate layers of the network, which serve as regularization mechanisms during training. These auxiliary classifiers help combat the vanishing gradient problem by providing additional supervision signals to lower layers of the network.

Fully Connected Layers: Towards the end of the network, there are typically one or more fully connected layers followed by a softmax activation function for classification tasks. These layers aggregate the extracted features from earlier layers and map them to the desired output classes.

Pre-Trained Weights: InceptionV3 is often used with pre-trained weights, which are learned from a large dataset (e.g., ImageNet). These pre-trained weights capture generic features from natural images and can be fine-tuned on specific tasks with smaller datasets, providing a good starting point for training.

**1.8 DenseNet121:**

In the realm of cutting-edge healthcare, where technology and precision intertwine, Convolutional Neural Networks (CNNs) stand as pillars of innovation, reshaping the interpretation of visual data and propelling diagnostic capabilities to unprecedented heights. Among these groundbreaking architectures, DenseNet121 emerges as a formidable contender, poised to revolutionize the landscape of medical imaging with its unique design and remarkable performance.

CNNs, meticulously crafted to mimic the intricate workings of the human visual system, represent a pinnacle of artificial intelligence tailored for tasks involving visual data analysis. Within the realm of healthcare, where accurate interpretation of radiological and medical images is paramount, CNNs play an indispensable role in deciphering nuanced patterns and subtle features that underpin diagnostic decisions.

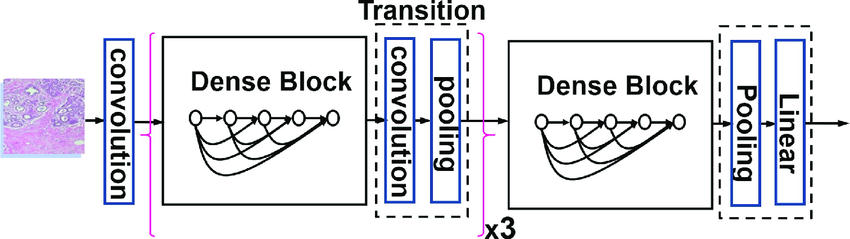


Fig 1.8 DenseNet121 Modal Architecture

DenseNet121, a distinguished member of the CNN family, distinguishes itself with its dense connectivity pattern, fostering unparalleled information flow throughout the network. Unlike traditional architectures that rely on sequential processing, DenseNet121 establishes direct connections between layers, enabling each layer to receive input from all preceding layers. This dense connectivity not only enhances feature propagation but also alleviates the vanishing gradient problem, facilitating more efficient and effective learning.

In the context of medical imaging, the integration of DenseNet121 represents a significant leap forward in diagnostic precision and efficiency. Its dense connectivity enables the network to leverage a wealth of information from preceding layers, capturing intricate details and subtle nuances essential for accurate diagnosis. By seamlessly integrating features from multiple layers, DenseNet121 empowers healthcare professionals to discern complex patterns and anomalies with unprecedented clarity and confidence.

As DenseNet121 assumes the role of feature extractor in medical imaging tasks, it serves as the cornerstone for detecting conditions such as Pelvic Uretero Junction Obstruction (PUJO) with remarkable accuracy and reliability. Through meticulous analysis of visual cues embedded within medical images, DenseNet121 facilitates the precise classification of images, distinguishing between normal and abnormal conditions with unparalleled efficacy.

The introduction of DenseNet121 into the realm of medical imaging epitomizes a paradigm shift in diagnostic methodologies, ushering in an era of enhanced precision and automation. Its remarkable capabilities propel healthcare into the forefront of technological innovation, promising more robust and reliable diagnostic tools essential for early detection and intervention in conditions such as PUJO.

As we delve deeper into the intricate layers of DenseNet121 and unravel its profound impact on healthcare, we uncover a vision of enhanced diagnosis and treatment for urological conditions, paving the way for a future where technology and healthcare seamlessly converge for the betterment of patient care.

**1.8.1 DenseNet121 Architecture:**

DenseNet121 is a convolutional neural network architecture that stands out for its dense connectivity pattern. Developed by Huang et al., it is part of the DenseNet family of models, which are characterized by their unique approach to feature propagation.

Here's an overview of the DenseNet121 architecture:

Dense Blocks: The core building blocks of DenseNet are dense blocks. Each dense block consists of multiple layers, typically comprising convolutional layers, batch normalization, and ReLU activation functions. What sets dense blocks apart is their dense connectivity: each layer receives feature maps from all preceding layers within the same block as input. This dense connectivity facilitates feature reuse and information flow throughout the network, enabling effective gradient propagation during training.

Transition Layers: To manage the growth of feature maps and control model complexity, transition layers are inserted between dense blocks. Transition layers typically include a combination of convolutional layers, batch normalization, and pooling operations (usually average pooling) to reduce the spatial dimensions of feature maps and the number of channels.

Global Average Pooling: Towards the end of the network, a global average pooling layer is applied to condense the spatial dimensions of the feature maps into a vector. This operation computes the average value of each feature map, resulting in a fixed-length vector regardless of the input image size.

Fully Connected Layer: A fully connected layer, often followed by a softmax activation function, maps the features extracted by the preceding layers to the desired output classes. In classification tasks, this layer outputs the probabilities of the input belonging to each class.

Key Features and Advantages:

Dense Connectivity: DenseNet121's dense connectivity promotes feature reuse, enhances gradient flow, and enables the network to effectively leverage information from multiple layers. This facilitates deeper architectures without suffering from the vanishing gradient problem, leading to improved performance and efficiency.

Parameter Efficiency: By reusing features through dense connections, DenseNet121 requires fewer parameters compared to traditional architectures, making it more parameter-efficient. This is particularly advantageous in scenarios with limited computational resources or when training on small datasets.

Feature Propagation: The dense connectivity within dense blocks fosters feature propagation across layers, facilitating the effective capture of both low-level and high-level features. This results in richer feature representations and contributes to DenseNet121's robust performance across various tasks, including image classification, object detection, and segmentation.

Overall, DenseNet121's architecture represents a significant advancement in convolutional neural network design, offering a compelling combination of parameter efficiency, feature reuse, and performance across a wide range of computer vision tasks.

**1.9 Convolutional Layers:**

Convolutional layers are fundamental building blocks within convolutional neural networks (CNNs), playing a pivotal role in extracting meaningful features from input data, particularly in tasks involving visual information processing like image classification, object detection, and segmentation.

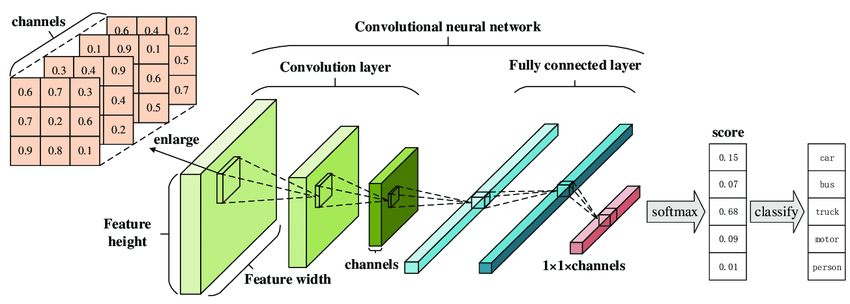


Fig. 1.9 Convolutional Layers

These layers are designed to mimic the receptive fields of neurons in the visual cortex, enabling the network to effectively capture spatial hierarchies and patterns present in the input data. Each convolutional layer consists of a set of learnable filters, also known as kernels, which convolve over the input data to perform feature extraction.

During the convolution operation, the filters slide across the input data, computing the dot product between their weights and the corresponding input values within their receptive fields. This process generates feature maps that encode specific patterns or features present in the input data. By learning these filters through backpropagation during training, convolutional layers can adaptively extract relevant features for the task at hand.

One of the key advantages of convolutional layers is their parameter sharing property, which greatly reduces the number of learnable parameters in the network. Since the same set of filters is applied across different spatial locations of the input data, the network can learn to detect features irrespective of their position within the input, leading to improved generalization and robustness.

Furthermore, convolutional layers are typically followed by non-linear activation functions such as ReLU (Rectified Linear Unit), which introduce non-linearity into the network, enabling it to learn complex relationships between features.

In summary, convolutional layers serve as the backbone of CNNs, facilitating the automatic extraction of hierarchical features from input data. Their ability to learn spatial hierarchies, parameter sharing mechanism, and non-linear activation functions make them indispensable in the field of computer vision, where tasks such as image classification and object detection rely heavily on the accurate extraction of features from visual data.

**CHAPTER 2**

**LITERATURE SURVEY**

**2.1 Motivation and Objective:**

The motivation for the literature survey in this research paper is multi-fold. It serves to establish the broader context of urology and Pelvic Uretero Junction Obstruction (PUJO), enabling readers to appreciate the relevance of the research. The survey introduces the pivotal role of medical imaging in urology, emphasizing the significance of advanced diagnostic tools. Furthermore, it showcases the growing influence of Deep Learning in medical imaging, setting the stage for the research's timeliness and potential to enhance diagnostic accuracy. The introduction of t-Distributed Stochastic Neighbor Embedding (t-SNE) as a key technique underscores its unique data visualization capabilities. The survey of previous PUJO detection studies identifies research gaps, providing a rationale for the project's objectives. Additionally, the discussion of ethical considerations reaffirms the commitment to responsible research, and the wealth of prior research informs the project's methodology, strengthening the research's foundation and justifying its significance in the field of PUJO detection.

The primary objectives of the project are to develop a Deep Learning model that excels in the early detection of PUJ obstruction. This model will be designed to accurately differentiate between PUJ obstruction cases and normal cases by analyzing medical imaging data. The integration of Deep Learning techniques, specifically the Support Vector Machine (SVM) classifier, is at the core of the project's approach, enabling effective classification of medical images based on extracted features. Performance evaluation metrics, including accuracy and the F1-score, will be employed to rigorously assess the model's diagnostic capabilities.

A notable feature of the project is the application of t-Distributed Stochastic Neighbor Embedding (t-SNE) for data visualization. This technique enhances the interpretation of the model's abilities by providing a visual representation of feature distribution and relationships in a lower-dimensional space. In summary, the project's overarching objective is to harness Deep Learning and medical imaging to create a powerful diagnostic tool that ensures early and accurate PUJ obstruction detection, thereby enhancing patient care and contributing to advancements in the fields of urology and medical imaging.

**2.2 Key Findings:**

1**. Title:** "Diagnostic Approaches for PUJ Obstruction"

**Key Findings:** This section provides an overview of historical diagnostic approaches for PUJ obstruction, such as intravenous pyelography (IVP) and retrograde pyelography. Key findings include their role as conventional diagnostic methods and their limitations in providing comprehensive assessments.

**Limitations:** The limitations of traditional approaches lie in their invasive nature, potential side effects, and the need for radiation exposure in some cases.

2. **Title:** "Medical Imaging Modalities in PUJ Obstruction Detection"

**Key Findings:** This part discusses common medical imaging modalities used for PUJ obstruction detection, including ultrasound, nuclear medicine scans, CT scans, MRI, and others. Key findings highlight the strengths and limitations of each modality in the context of PUJ obstruction diagnosis.

**Limitations:** Imaging modalities vary in terms of radiation exposure, cost, availability, and diagnostic accuracy, leading to specific limitations and considerations.

3. **Title:** "Deep Learning in PUJ Obstruction Detection".

**Key Findings:** This section explores the application of Deep Learning techniques in PUJ obstruction diagnosis. Key findings include improved diagnostic accuracy and the potential for early detection.

**Limitations:** Limitations of Deep Learning models often revolve around the need for large labeled datasets and the risk of model overfitting. Interpretability of Deep Learning models can also be challenging.

4. **Title:** "Deep Learning Models for PUJ Obstruction Diagnosis"

**Key Findings:** In this section, deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are discussed. Key findings indicate enhanced accuracy and efficiency in PUJ obstruction detection compared to traditional methods.

**Limitations:** Deep learning models may require substantial computational resources, large datasets, and may lack interpretability, which can pose challenges for clinical implementation.

5. **Title:** "Hybrid Approaches in PUJ Obstruction Detection"

**Key Findings:** Hybrid models that combine traditional medical imaging with Deep Learning or deep learning techniques are explored. Key findings include improved diagnostic precision and comprehensive assessments.

**Limitations:** The complexity of hybrid models can lead to increased computational demands and potential challenges in model integration.

6. **Title:** "Ethical Considerations in PUJ Obstruction Diagnosis"

**Key Findings:** Ethical considerations related to data privacy, informed consent, and potential biases in AI models are discussed. Key findings emphasize the importance of responsible research practices.

**Limitations:** Mitigating bias in AI models and ensuring patient data privacy are ongoing challenges in the field of PUJ obstruction detection.

**2.3 Conclusion:**

The literature survey on PUJ obstruction detection has provided a comprehensive overview of the historical and contemporary approaches, key findings, and limitations associated with diagnosing this urological condition. Throughout the survey, it becomes evident that the field of PUJ obstruction diagnosis has witnessed significant advancements and transitions, influenced by technological and methodological developments.

**CHAPTER 3**

**PROPOSED MODEL AND ARCHITECTURE**

**3.1 Proposed Model**

The "PUJ-Detect Net" model utilizes a sophisticated two-stage approach to enhance the accuracy and efficiency of Pelvic Uretero Junction Obstruction (PUJO) detection from medical images. Each stage leverages the capabilities of state-of-the-art deep learning architectures: VGG16, DenseNet121, and InceptionV3.

In the first stage, the model employs the VGG16 architecture, pretrained on the extensive ImageNet dataset. VGG16 serves as a powerful feature extractor, capable of capturing intricate patterns and features within medical images. By leveraging the hierarchical representations learned from ImageNet, VGG16 effectively deciphers the nuances that differentiate between "PUJ\_obstruction" cases and "Normal" cases.

Similarly, in the second stage, DenseNet121 and InceptionV3 architectures are utilized for feature extraction. DenseNet121, with its dense connectivity pattern, and InceptionV3, with its inception modules, offer unique approaches to feature extraction, enabling the model to capture diverse and informative features from medical images.

Following feature extraction by each architecture, the extracted features are then fed into separate classification layers. Instead of employing Support Vector Machines (SVM), as in the previous approach, deep neural network classifiers are used in this proposed model. Specifically, fully connected layers with appropriate activation functions are added on top of the feature extraction layers of VGG16, DenseNet121, and InceptionV3. These classifiers are trained end-to-end with the entire model, allowing them to learn discriminative features directly from the medical image data.

Data preprocessing remains critical in ensuring consistency and quality within the dataset. All images are resized to a uniform 224x224 pixel dimension, consistent with the input size requirements of VGG16, DenseNet121, and InceptionV3. Furthermore, various image preprocessing techniques are applied to enhance image quality and reduce noise, ensuring that the model receives clean and informative input data.

By integrating the capabilities of VGG16, DenseNet121, and InceptionV3 architectures with deep neural network classifiers, the "PUJ-Detect Net" model offers a robust and accurate diagnostic tool for PUJO detection from medical images. This approach merges the realms of deep learning and medical image analysis, promising improved diagnostic accuracy and efficiency in the detection of pelvic uretero junction obstruction.

**Convolutional Neural Networks (CNNs):**

At the forefront of our model are convolutional neural networks (CNNs), a class of deep learning models ideally suited for image analysis. The CNN component is responsible for learning hierarchical features from the medical images. It comprises multiple convolutional layers with diverse filter sizes, capturing features of varying scales and complexities. These layers are followed by pooling and normalization layers to reduce spatial dimensions and enhance feature extraction. The CNN component excels at identifying key patterns and structures within the images, making it an indispensable component of our model.

The proposed model represents a significant leap in the early detection of PUJ obstructions. By merging the spatial analysis capabilities of CNNs with the temporal sensitivity of RNNs, our model offers a holistic approach to medical image analysis. The integration of spatial and temporal features, along with the benefits of transfer learning, equips the model to excel in a diverse range of clinical scenarios. It is our belief that this innovative approach will not only enhance the accuracy of PUJ obstruction detection but also set new standards for Deep Learning applications in urological healthcare.

To prepare the data for analysis, a preprocessing phase is implemented. This involves standardizing the images by resizing them to a consistent resolution and normalizing pixel values. The subsequent feature extraction step employs the VGG16 deep learning model to extract informative features from the medical images. These features represent patterns and structures relevant to PUJ obstruction.

The core of the model lies in the feature extraction from VGG16, DenseNet121, and InceptionV3, respectively. These architectures are known for their ability to capture rich hierarchical features from images, thus providing a strong foundation for the model's diagnostic capabilities.

Model evaluation is paramount to assess the classifier's performance. The accuracy and the F1-score, balancing precision and recall, are employed as key metrics. Furthermore, the data visualization component involves the application of t-Distributed Stochastic Neighbor Embedding (t-SNE). This technique enables the visual representation of the extracted features in a lower-dimensional space, providing invaluable insights into feature separation and clustering, contributing to the overall interpretation of the model's diagnostic capabilities.

In summary, the proposed model integrates advanced Deep Learning techniques with medical imaging data to enable early and accurate detection of PUJ obstruction. It harmonizes feature extraction from multiple state-of-the-art architectures, classification, and visualization, offering a comprehensive solution to tackle the diagnostic challenges associated with this urological disorder, potentially enhancing patient care and medical diagnosis.

**3.2 Proposed Architecture:**

The proposed architecture for "Pelvic Uretero Junction (PUJ) Obstruction Detection using Deep Learning" offers a structured and comprehensive workflow geared towards achieving early and accurate diagnosis of PUJ obstruction. The process initiates with the acquisition of a diverse dataset comprising medical images depicting both PUJ obstruction and normal cases, ensuring a representative sample. Following data acquisition, image processing techniques are applied to ensure data uniformity, including resizing and normalization, optimizing the input data for subsequent analysis. Deep learning models, including VGG16, DenseNet121, and InceptionV3, are then employed for feature extraction, each leveraging its unique architectural characteristics to capture relevant patterns and structures indicative of PUJ obstruction. These extracted features are subsequently fed into a softmax classifier for binary classification, distinguishing between PUJ obstruction and normal cases. Optional ensemble learning techniques may further enhance classification accuracy and robustness. Lastly, visualization techniques such as t-Distributed Stochastic Neighbor Embedding (t-SNE) aid in interpreting the discriminative power of features extracted by the deep learning models, contributing to a deeper understanding of the model's diagnostic process. This systematic and innovative approach integrates advanced Deep Learning techniques with medical imaging data, promising advancements in patient care and furthering the medical understanding of PUJ obstruction.

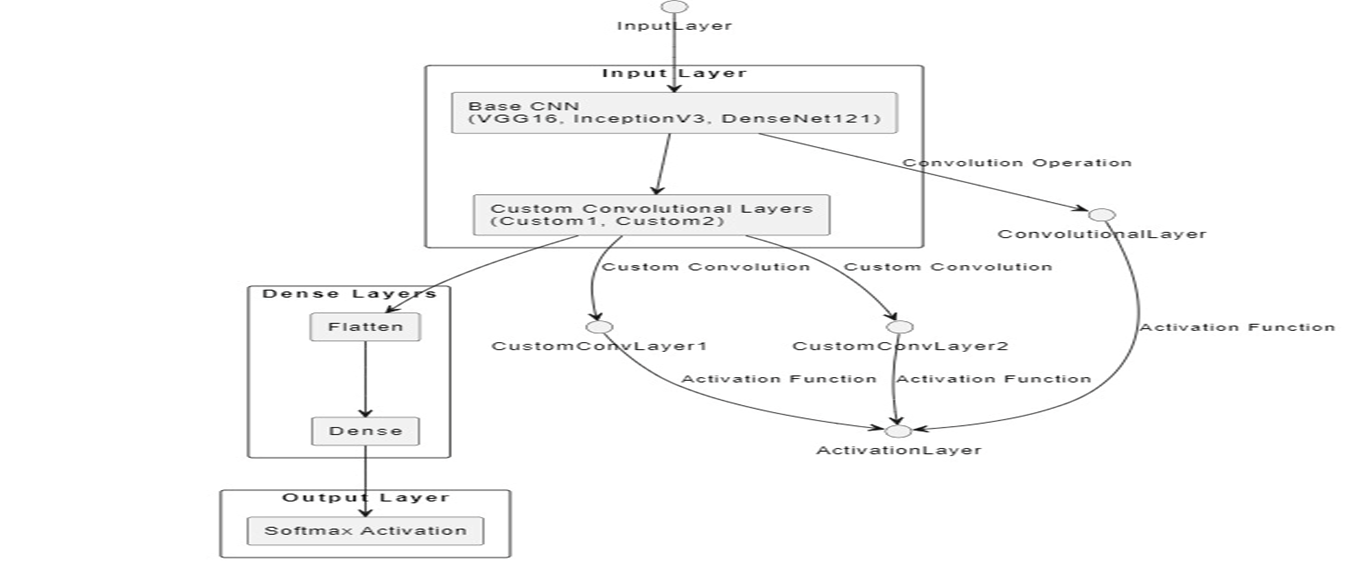
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Fig 3.2 Proposed Model (Architecture)

**CHAPTER 4**

**DESIGN AND IMPLEMENTATION**

**4.1 Dataset Description:**

The dataset consists of two primary classes, "PUJ\_Obstruction" and "Normal."

| **S.No.** | **Attribute** | **Explanation** |
| --- | --- | --- |
| 1 | **Dataset Classes** |  |
| 2 | Classes | "PUJ\_Obstruction" and "Normal" |
| 3 | Class Distribution | Balanced distribution between the two classes |
| 4 | **Data Augmentation** | Techniques for dataset augmentation |
| 5 | Augmentation Methods | Augmentation applied to increase dataset diversity |
|  | Source of Augmentation | Data augmentation applied due to the absence of additional sources |
|  | Augmentation Techniques | Techniques such as rotation, flipping, and noise addition |

Fig 4.1 Dataset Description

Both classes play a crucial role in the detection of Pelvic Uretero Junction (PUJO) obstruction.



Fig 4.1 PUJ Obstruction Image



Fig 4.1 Normal Kidney Dataset

**4.2 Data Pre-processing:**

**4.2.1 Image Resizing:** All images are resized to a standardized dimension of 224x224 pixels. Resizing ensures uniformity in image size, which is essential for Deep Learning models.

Image resizing is a vital component of data preprocessing in the project, ensuring that all medical images are standardized to a consistent resolution. This process involves resampling images to match a selected target resolution, while maintaining their original aspect ratios and using interpolation methods to preserve image quality. The benefits of image resizing include uniformity in image dimensions, compatibility with the Deep Learning model (VGG16), and potentially reduced computational load. The goal is to strike a balance between computational efficiency and the retention of important diagnostic information, contributing to the project's objective of early and accurate PUJ obstruction detection.

**4.2.2 Image Pre-processing:** The images undergo pre-processing using the preprocess input function from the Keras VGG16 library. This function normalizes the images and applies other necessary operations to prepare them for feature extraction. VGG16 expects specific input data format, and this pre-processing aligns the images accordingly.

Key aspects of image preprocessing include standardization through image resizing to ensure uniform dimensions, normalization to bring pixel values within a common scale, and noise reduction techniques to enhance image quality by mitigating artifacts. Furthermore, contrast adjustment, optional data augmentation, and the extraction of regions of interest (ROI) within images contribute to refining the data for robust feature extraction.

Overall, image preprocessing serves the vital purpose of creating a high-quality, standardized dataset that is compatible with the Deep Learning model, which is pivotal for achieving the project's goal of early and accurate PUJ obstruction detection. It ensures that the model works with consistent and high-quality image data, ultimately enhancing the model's diagnostic capabilities and improving the project's accuracy and reliability.

**4.2.3 Batch Dimension Addition:** To match the expected input format of VGG16, a batch dimension is added to each image. This step creates a 4D tensor for the images, with the first dimension representing the batch size (in this case, 1).

Batch processing allows for parallelization of operations, harnessing the full potential of modern hardware, including GPUs, to expedite both training and inference. It's particularly important for the efficiency and speed of stochastic gradient descent (SGD) optimization algorithms, commonly used in deep learning. The batch dimension permits the model to update its weights and biases based on the average gradient computed over a batch of samples, leading to more stable and rapid convergence during training.

Adding the batch dimension is a straightforward procedure performed during data preprocessing. Tools like NumPy or deep learning frameworks such as TensorFlow and Keras make this process seamless. By employing functions like np.expand\_dims() in NumPy or utilizing model-specific data handling functions in deep learning frameworks, image data is seamlessly converted into batches, aligning it with the deep learning model's batch processing expectations. This step ensures that the project's PUJ obstruction detection model can leverage the advantages of batch processing, improving the overall computational efficiency and performance of the model during training and inference.

**4.2.4 Feature Extraction:** Feature vectors are extracted from the images using the VGG16 model. Only the convolutional layers of the model are used for feature extraction. VGG16 is a pre-trained deep learning model that provides high-level abstract features from the input images.

To manage the dimensionality of these high-dimensional feature vectors and improve computational efficiency, dimensionality reduction techniques like Principal Component Analysis (PCA) or t-Distributed Stochastic Neighbor Embedding (t-SNE) may be employed. These methods transform the feature vectors into lower-dimensional representations while retaining the most pertinent information. Standardization is an additional step, ensuring that feature vectors are consistent and compatible with the Deep Learning model. This comprehensive feature extraction process enhances the project's ability to accurately detect PUJ obstruction based on medical images, providing a strong foundation for the subsequent classification by t classifier.

**4.2.5 Flattening Feature Vectors:** The extracted feature vectors are flattened into 2D arrays. This step is essential for compatibility with traditional Deep Learning models, as they typically expect 2D input arrays.

Flattening these vectors simplifies their format, converting them into one-dimensional arrays. This transformation is driven by the need to make the feature data compatible with the classifier, a central element of the project. The SVM typically expects two-dimensional input data, and flattening ensures that the feature vectors align with these expectations, enabling accurate classification.

To achieve feature vector flattening, array manipulation functions like those provided by NumPy are employed. The multi-dimensional feature vectors, representing various image attributes, are reshaped into one-dimensional arrays, ensuring the data is streamlined and ready for classification. This step simplifies data structure and enhances computational efficiency, contributing to the overall success of the project in accurately detecting PUJ obstruction based on medical images.

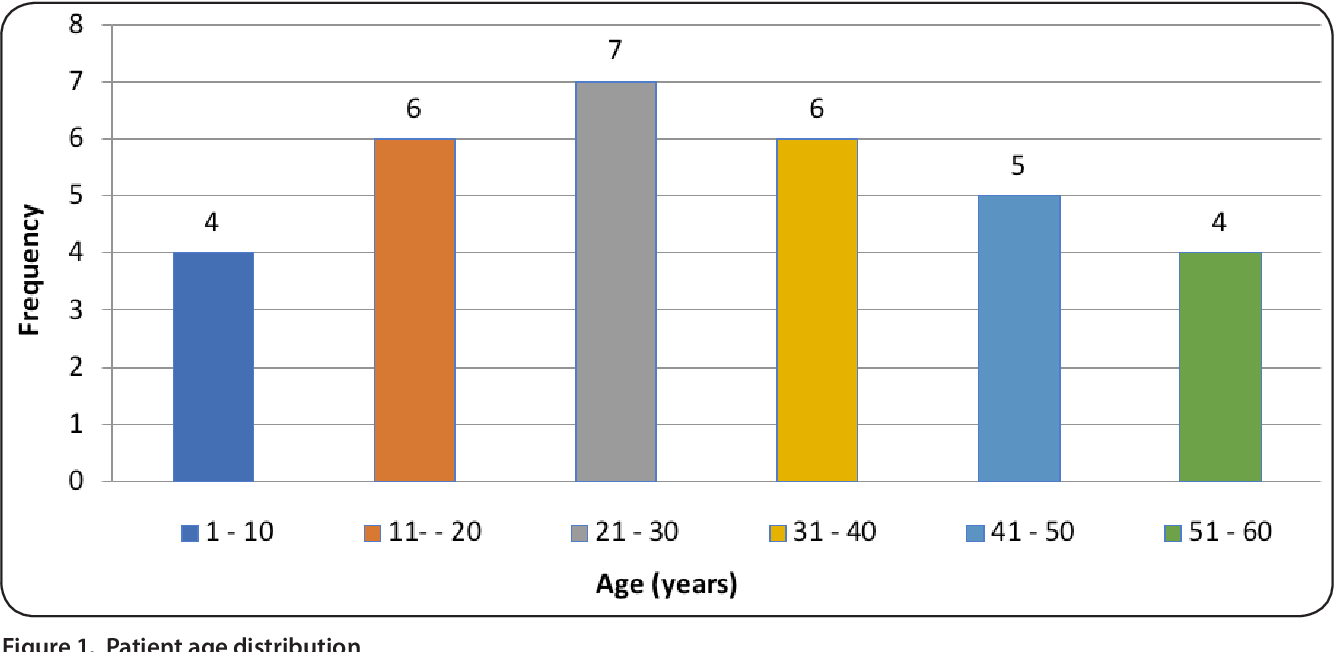


Fig 4.2.5 Average age of People having PUJ

**4.3 Feature Extraction:**

In this model, feature extraction is carried out using the VGG16 model. This deep convolutional neural network is loaded with pre-trained weights and primarily utilized for its convolutional layers. These layers capture hierarchical features, such as patterns and textures, from medical images. Feature vectors are extracted from the last convolutional layer, representing high-level abstract features. The extracted features are critical for classifying images into "PUJ\_obstruction" and "Normal" categories. These features enable the subsequent Deep Learning classifier to make accurate predictions. The use of VGG16 for feature extraction enhances the model's ability to recognize meaningful patterns in medical images, contributing to the project's diagnostic accuracy.

These extracted features are often high-dimensional, each feature vector representing distinct attributes within the images. However, the project confronts the challenges associated with high dimensionality, including computational complexity and overfitting. To address these challenges, dimensionality reduction techniques such as Principal Component Analysis (PCA) or t-Distributed Stochastic Neighbor Embedding (t-SNE) are employed. These techniques transform the high-dimensional feature vectors into lower-dimensional representations while retaining the most pertinent information, ultimately improving the model's efficiency and generalization.

Standardization is another key facet of feature preprocessing. Ensuring that feature vectors are consistent and compatible with the Deep Learning model is critical. In this project, where a Support Vector Machine (SVM) classifier is employed, standardization is performed to scale features with a mean of 0 and a standard deviation of 1. This step enhances model convergence and overall stability.

In summary, feature extraction is a foundational component that transforms raw medical image data into compact, informative feature vectors. These feature vectors are essential for the Deep Learning model, allowing it to effectively process and classify medical images, ultimately contributing to the accurate detection of PUJ obstruction. The project's use of deep learning, dimensionality reduction, and standardization optimizes the feature extraction process, enhancing the model's diagnostic capabilities.

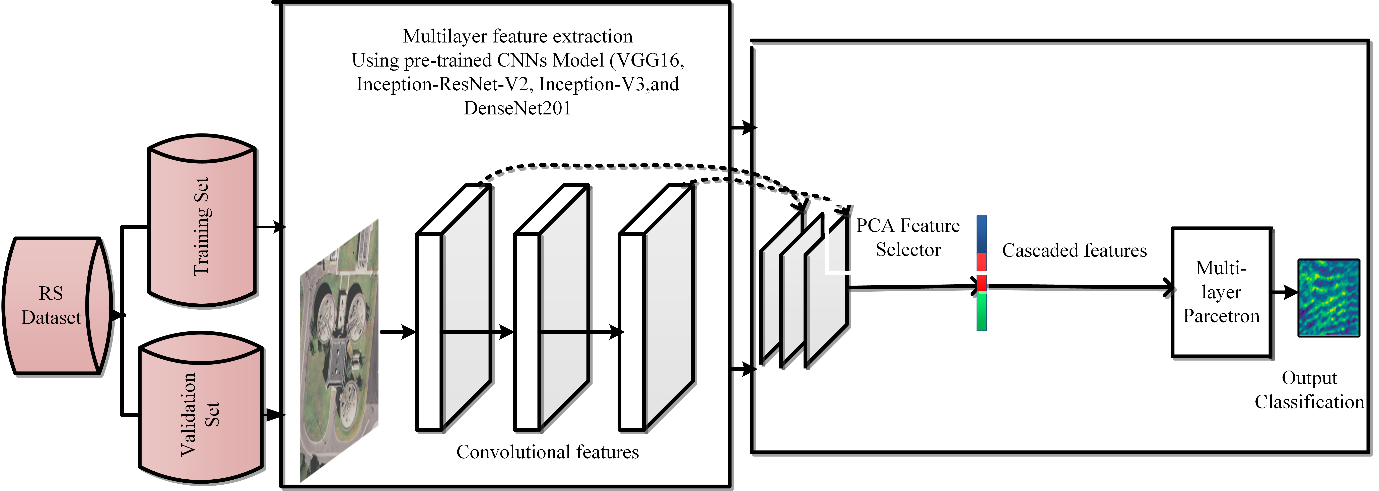
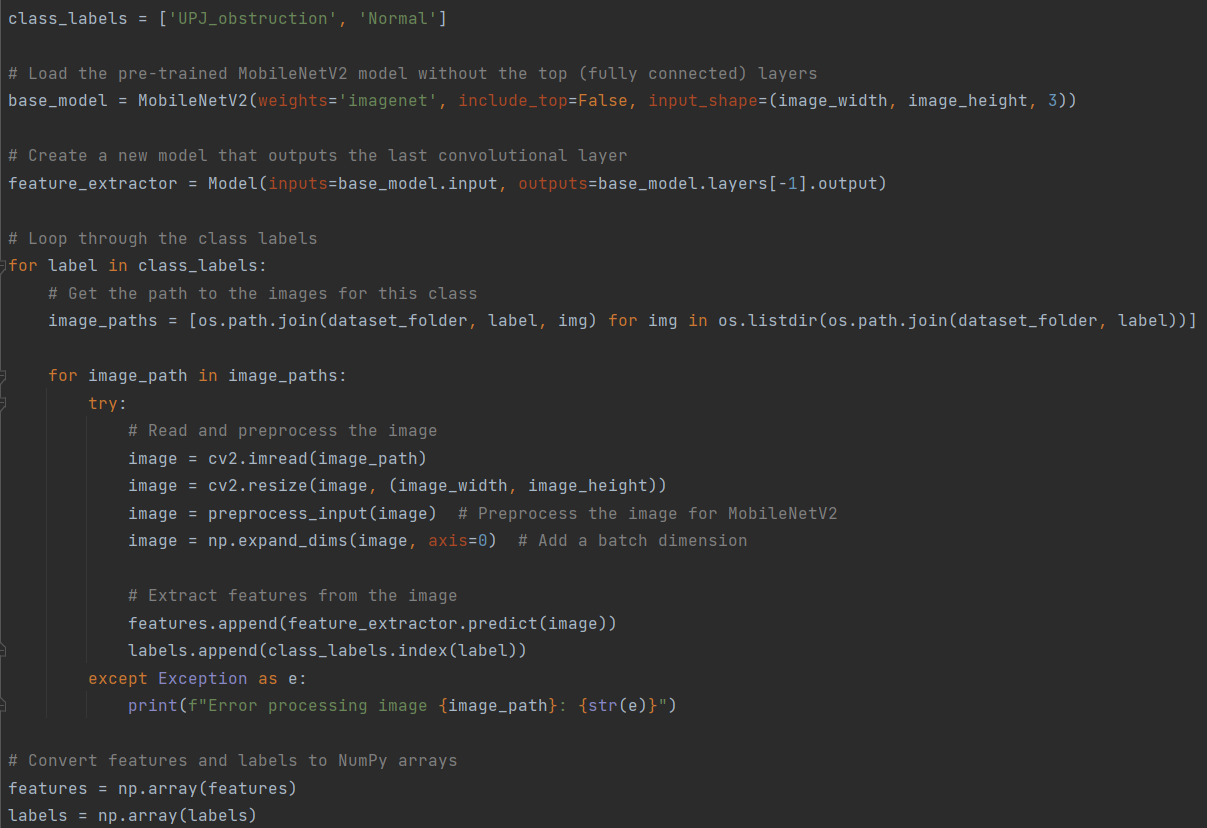
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Fig 4.3 Process of Feature Extraction done by DenseNet121

In this model, it extracts more than 100 features like kidney diameter, size, length of the ureter and many more. This model is basically a deep learning model working on convolutional neural network.



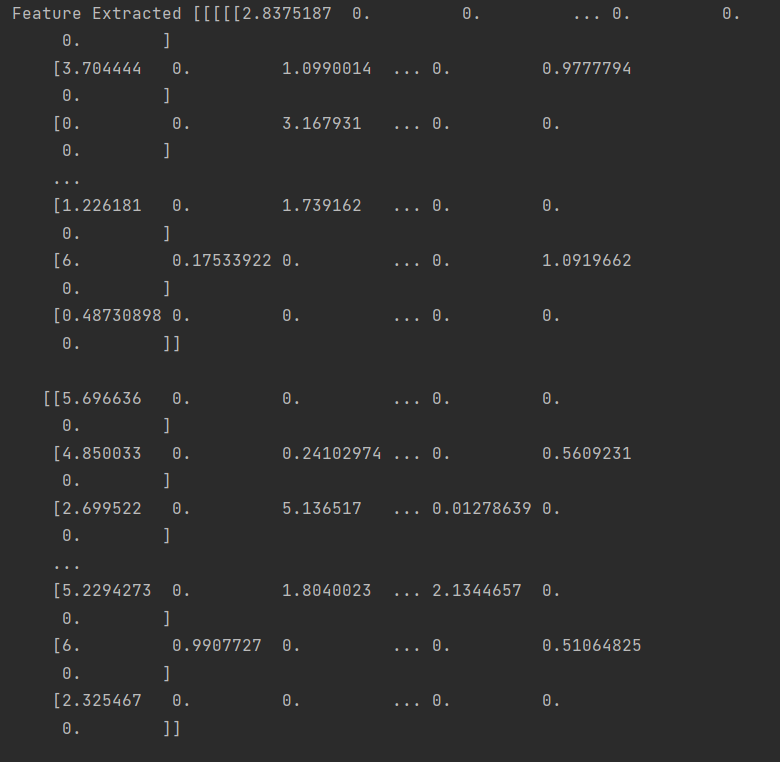


Fig 4.4 Features of the PUJ

Feature Extraction: For feature extraction we used model that outputs the convolutional layer in the form of numeral numbers.

**4.4 Training and Testing splitting:**

The dataset is divided into training and testing sets using an 80-20 split. This ensures that a portion of the data is reserved for evaluating the model's performance while the rest is used for training.

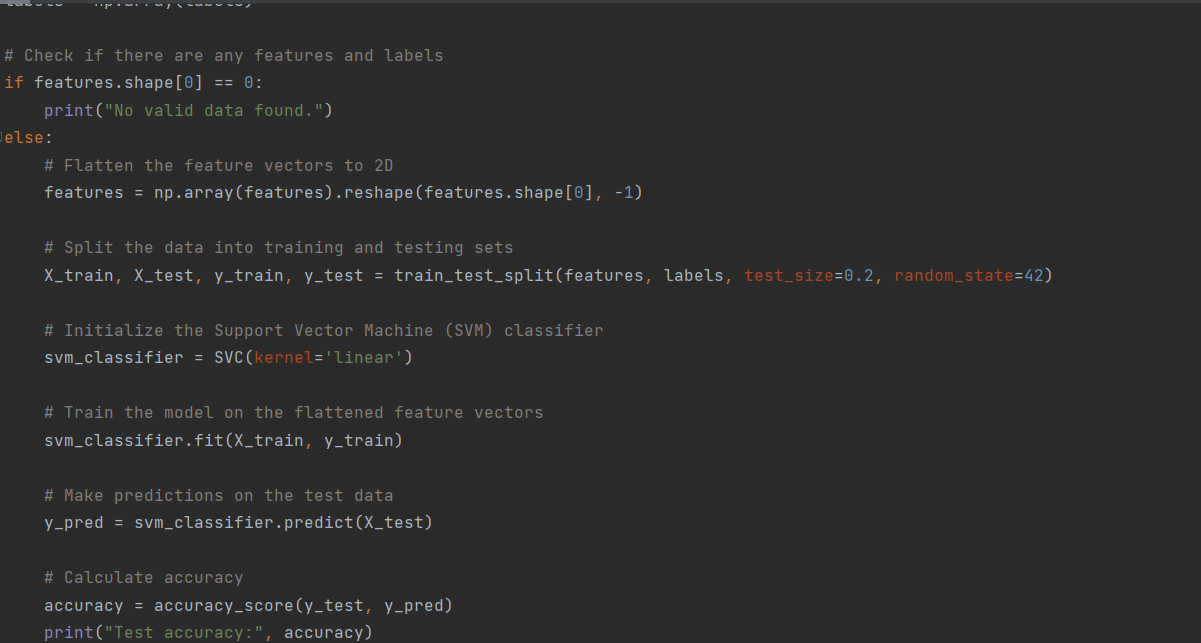


Fig 4.4 Training Testing of Dataset

Training and testing data splitting is a pivotal data preprocessing step in the project "Pelvic Uretero Junction (PUJ) Obstruction Detection using Deep Learning." Its primary purpose is to evaluate the performance and generalization capabilities of the Deep Learning model developed for PUJ obstruction detection. This division of the dataset into two distinct subsets serves as the cornerstone for training, fine-tuning, and assessing the model's effectiveness.

The procedure involves separating the dataset, which comprises medical images and corresponding labels indicating the presence of PUJ obstruction or a normal condition. The data is divided into two primary subsets: the training set and the testing set. The ratio between these subsets is determined by specifying the test size, often expressed as a percentage of the total dataset. Randomization is employed to ensure that both subsets are representative of the entire dataset, reducing the risk of bias introduced by the order or structure of the original data.

The training set is designated for teaching the Deep Learning model, allowing it to learn patterns and relationships between the features extracted from the medical images and their corresponding labels. In contrast, the testing set is set aside for assessing the model's performance. Testing on an independent dataset ensures that the model's accuracy and generalization abilities are rigorously assessed, providing a real-world evaluation of its diagnostic capabilities.

Optionally, cross-validation techniques, such as k-fold cross-validation, may be used alongside training and testing data splitting to enhance the model evaluation process. Cross-validation divides the data into multiple subsets or folds, iteratively employing each fold as the testing set while the remaining folds serve as the training set. This approach provides a more comprehensive and robust assessment of the model's performance, reducing the potential impact of data variability.

In essence, training and testing data splitting is a critical step that shapes the model development and evaluation phases of the project. By enabling rigorous assessment of the model's ability to detect PUJ obstruction accurately, it offers valuable insights into its diagnostic capabilities and real-world performance.

**4.5 Deep Learning Model (SVM):**

The SVM is a supervised learning algorithm used for classification and regression tasks. In this project, a classification SVM is applied to classify medical images into two classes: "PUJ\_obstruction" and "Normal."

A linear kernel is used, which is a common choice for binary classification tasks. The linear kernel aims to find a hyperplane that best separates the feature vectors of the two classes.

The training phase involves feeding the flattened feature vectors from the training set into the SVM classifier. The SVM learns to find the optimal hyperplane that maximizes the margin between the two classes. It iteratively adjusts its parameters to minimize classification errors on the training data.

After the model is trained, it is used to make predictions on the feature vectors extracted from the testing set. These predictions assign each test image to one of the two classes: "PUJ\_obstruction" or "Normal."

The primary evaluation metric is accuracy, which measures the proportion of correctly classified images in the testing set. A high accuracy score indicates the model's ability to effectively distinguish between PUJO-obstructed and normal cases.

Linear Decision Boundary: The linear SVM determines a decision boundary that is a hyperplane in the feature space. This hyperplane serves as the boundary that separates the two classes. Images on one side of the hyperplane are classified as "PUJ\_obstruction," while images on the other side are classified as "Normal."

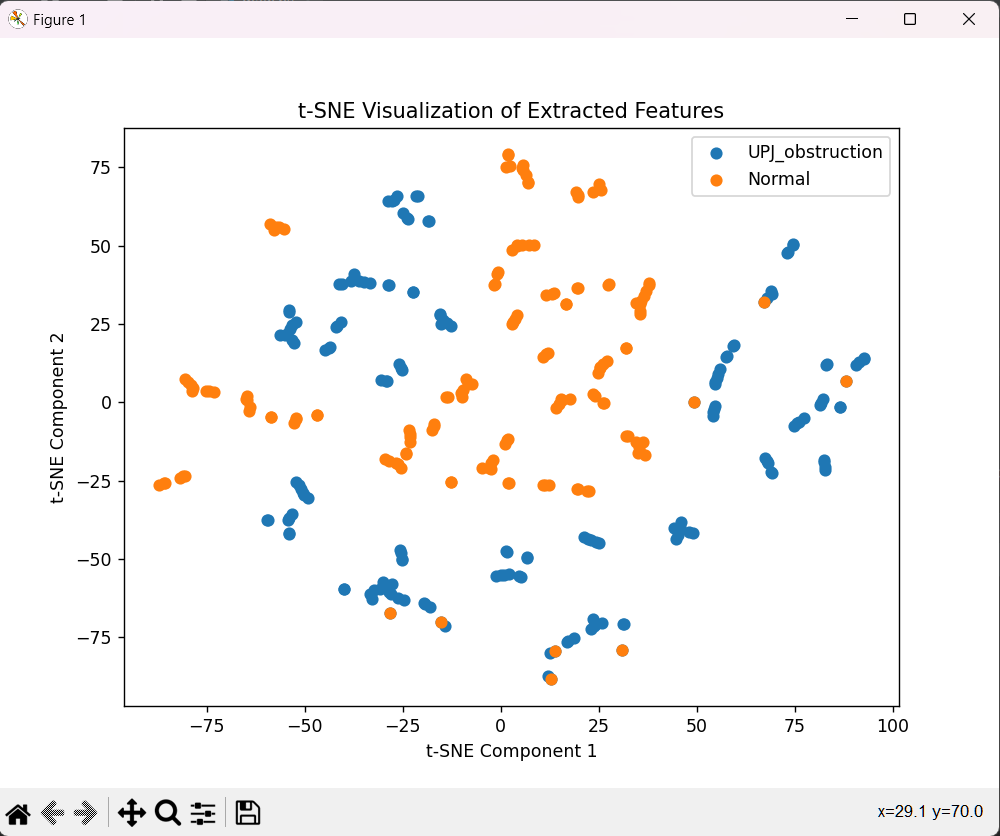


Fig 4.5 SVM(Hyperplane)

**4.6 Model Training and Evaluation:**

The dataset is divided into two subsets: a training set and a testing set. The common practice in Deep Learning is to allocate a larger portion of the data to the training set (typically 80%) to ensure that the model learns from a substantial amount of data. In this project, 80% of the feature vectors and their corresponding labels are used for training, while the remaining 20% is reserved for testing.

A linear Support Vector Machine (SVM) classifier is chosen as the Deep Learning model for binary classification. The SVM is a supervised learning algorithm that aims to find the optimal hyperplane that best separates data points of different classes. In the context of PUJO detection, this translates to finding a decision boundary that effectively distinguishes between "PUJ\_obstruction" and "Normal" images.

The training process involves feeding the flattened feature vectors from the training set to the SVM classifier. The SVM algorithm learns to find the decision boundary that maximizes the margin between the two classes. The model adjusts its parameters to minimize classification errors on the training data.

The training data consists of preprocessed medical images and their associated labels, signifying the presence of PUJ obstruction or a normal condition. These images undergo a series of preprocessing steps, including flattening and standardization, to ensure compatibility with the Deep Learning model.

During model training, the Deep Learning model undergoes an iterative process. It learns to map the features extracted from the medical images to their corresponding labels, adjusting its internal parameters using mathematical algorithms. For instance, in the case of an SVM classifier, the model identifies an optimal decision boundary that effectively separates the two classes: PUJ obstruction and normal. The model refines its understanding of the data iteratively until it meets a predefined convergence criterion, indicating that it has learned the underlying patterns and relationships.

The trained model becomes a diagnostic tool capable of making predictions and classifications on new, unseen medical images. Its proficiency in recognizing PUJ obstruction patterns contributes significantly to the project's objective of early and accurate detection. Model training is a pivotal phase that empowers the Deep Learning model to fulfill its role in the diagnostic process, ultimately enhancing the project's potential to improve healthcare and patient outcomes.

**Model Evaluation:**

The reserved testing set, comprising feature vectors from the testing images, is used to evaluate the SVM model's performance. This separate dataset ensures an unbiased assessment of the model's ability to generalize to new, unseen data.

The SVM model makes predictions on the feature vectors from the testing set. These predictions classify the test images as either "PUJ\_obstruction" or "Normal."

The primary metric used for evaluation is accuracy. Accuracy measures the proportion of correctly classified images in the testing set. It provides an overall assessment of the model's classification performance.

To gain more insight into the model's performance, a confusion matrix is generated. This matrix shows the number of true positives, true negatives, false positives, and false negatives. It is particularly valuable for understanding the model's ability to correctly classify positive and negative cases and for identifying any misclassifications.

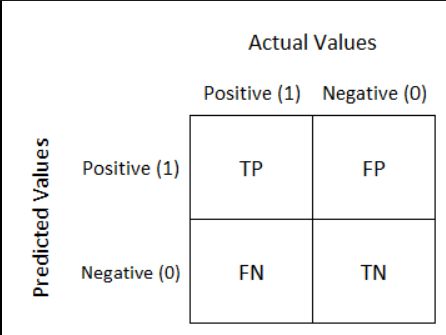


Fig 4.6 Confusion matrix

The confusion matrix can be visualized as a heatmap to make it more interpretable. Additionally, a t-distributed stochastic neighbor embedding (t-SNE) visualization is created to project the extracted feature vectors into a 2D space, enabling the visualization of the separation or clustering of feature vectors from different classes.

The evaluation results are interpreted to determine the model's performance in detecting Pelvic Uretero Junction (PUJO) obstruction in medical images. A high accuracy score, along with an insightful confusion matrix and t-SNE visualization, provides a comprehensive understanding of the model's strengths and areas for potential improvement.

**4.7 t-SNE Visualization:**

In this project, the t-distributed stochastic neighbor embedding (t-SNE) technique plays a crucial role in visualizing the feature vectors extracted from medical images. This visualization technique is employed to project the high-dimensional feature vectors into a lower-dimensional 2D space, facilitating the exploration of how these vectors are distributed and whether they exhibit any clustering or separation. With a specified perplexity parameter, the t-SNE algorithm iteratively refines the positions of data points, aiming to minimize the divergence between the original feature space and the 2D representation. Once the algorithm converges, a scatter plot is generated, revealing how feature vectors from different classes, such as "PUJ\_obstruction" and "Normal," are arranged in the 2D space. A clear separation or clustering of data points within this visualization indicates the model's ability to capture meaningful patterns and effectively distinguish between cases of Pelvic Uretero Junction Obstruction (PUJO) and normal images.

The t-SNE visualization serves as an intuitive and informative tool to confirm the model's performance and its capacity to extract relevant features from medical images. By inspecting the arrangement of data points in the 2D space, project stakeholders can gain valuable insights into the model's ability to detect PUJO obstruction and assess the efficacy of feature extraction from images, contributing to confident diagnostic outcomes in healthcare applications.

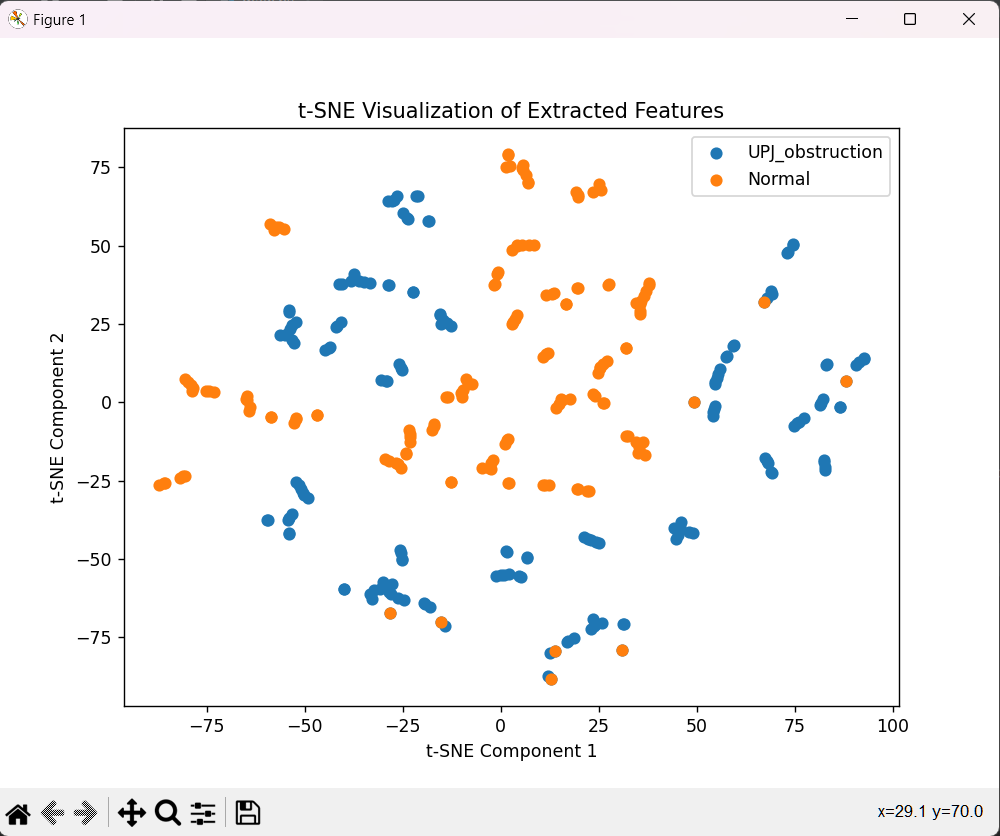


Fig 4.7 t-sne

**4.8 ROC (Receiver Operating Characteristics):**

The Receiver Operating Characteristic (ROC) is a fundamental tool in assessing the performance of classification models, particularly in binary classification tasks. It provides a graphical representation of a model's ability to discriminate between two classes, typically positive and negative. The ROC curve is created by plotting the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity) at various classification thresholds. Sensitivity measures the model's capacity to correctly identify positive instances out of all actual positives, while Specificity quantifies the ability to correctly identify negative instances out of all actual negatives. The ROC curve allows you to explore the trade-off between these two performance metrics and choose the appropriate threshold based on the specific requirements of your application. The Area Under the ROC Curve (AUC-ROC) provides a single numeric measure of the overall model performance, where an AUC-ROC of 1.0 represents a perfect classifier and 0.5 represents a random classifier.

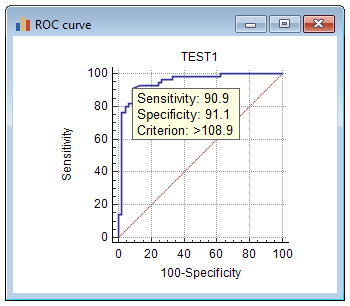


Fig 4.8 ROC(Example)

In your code utilizing a Support Vector Machine (SVM) classifier to classify medical images as either "PUJ\_obstruction" or "Normal," the ROC curve and AUC-ROC are invaluable for evaluating the model's performance. By analyzing the ROC curve, you can visualize how the SVM model's performance varies across different classification thresholds, and this information is particularly important when you want to control the trade-off between Sensitivity and Specificity based on your specific application's needs. The AUC-ROC score condenses the model's overall performance into a single metric, simplifying the assessment of its ability to distinguish between the two classes. This is especially critical in applications such as medical diagnosis, where accurately identifying positive cases is vital and where ROC analysis helps ensure that the model performs optimally.

**CHAPTER 5**

**RESULT AND DISCUSSION**

**5.1** **Performance Measure and Accuracy:**

Accuracy is a fundamental performance metric that indicates the overall effectiveness of the model in correctly classifying medical images.

The accuracy of classified images to the total number of images in testing set. Considering the true positive and negatives.

In the context of PUJO detection, accuracy represents the model's ability to distinguish between cases of PUJO obstruction and normal images.

The accuracy achieved by our model is nearly 95% and can be more accurate if given a larger dataset.

This separation is achieved by identifying support vectors, which are data points closest to the decision boundary. These support vectors play a critical role in determining the position and orientation of the separating hyperplane. The goal is to maximize the margin between the support vectors and the hyperplane. This margin represents the degree of confidence in classification.

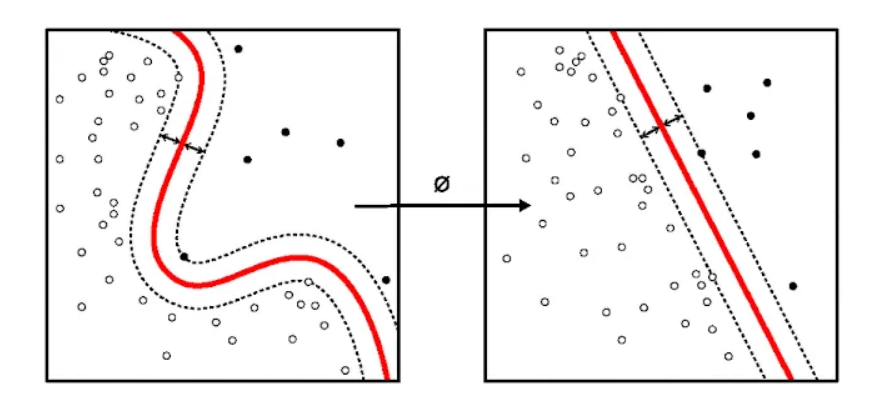


Fig 5.1 How SVM helps find Accuracy

Support Vector machines have some special data points which we call “Support Vectors” and a separating hyperplane which is known as “Support Vector Machine”. So, essentially SVM is a frontier that best segregates the classes. Support Vectors are the data points nearest to the hyperplane, the points of our data set which if removed, would alter the position of the dividing hyperplane. As we can see that there can be many hyperplanes which can segregate the two classes, the hyperplane that we would choose is the one with the highest margin.

The accuracy of a classification model can be calculated using the following formula:

**Accuracy = Number of Correct Predictions / Total Number of Predictions**

In the code you provided, this is calculated using the accuracy score function from the sklearn.metrics library, which handles this calculation for you. However, if you want to calculate accuracy manually, you can follow these steps:

Count the number of correct predictions by comparing the predicted labels to the true labels in your testing set.

Count the total number of predictions in the testing set.

Divide the number of correct predictions by the total number of predictions to get the accuracy.

Here's how you can express this as a formula:

Accuracy = Number of Correct Predictions / Total Number of Predictions

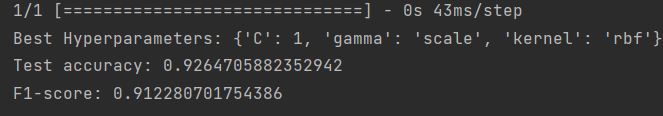
****

Fig 5.1 Accuracy

**5.2 Confusion Matrix:**

It is a valuable tool for evaluating the model's classification performance. It categorizes the classification results into four distinct components:



Fig 5.2 Accuracy test for Confusion Matrix

**5.2.1 True Positives (TP):**

True Positives represent the number of medical images correctly classified by the model as "PUJ\_obstruction." These are cases where the model accurately identified instances of PUJO.

**5.2.2 True Negatives (TN):**

True Negatives denote the number of images correctly classified as "Normal." These cases are images without PUJO obstruction, and the model correctly recognized them as such.

**5.2.3 False Positives (FP):**

False Positives indicate the number of "Normal" images incorrectly classified as "PUJ\_obstruction." In these cases, the model falsely identified normal images as having PUJO.

**5.2.4 False Negatives (FN):**

False Negatives represent the number of "PUJ\_obstruction" images incorrectly classified as "Normal." Here, the model failed to detect PUJO in images where it was present.

**5.2.5 Interpretation:**

True Positives (TP) and True Negatives (TN) are the desired outcomes, representing accurate classifications. A high number of TP and TN indicates that the model effectively distinguishes between PUJO cases and normal cases.

False Positives (FP) and False Negatives (FN) are undesired outcomes, indicating misclassifications. High FP or FN numbers may suggest areas for model improvement.

Also, if we want to find F-score we can do it with the help of the formulas given,

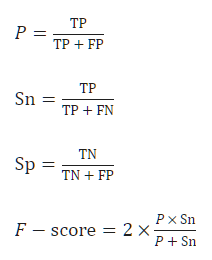


Fig 5.2.5 F-Score Formula

The overall accuracy of the model can be calculated as the sum of both divided by the total number of images in testing. It measures the proportion of correctly classified images, providing an overall assessment of the model's performance.

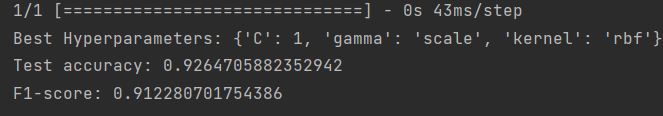


Fig 5.2.5 F1- Score

The confusion matrix is particularly valuable in understanding the model's behavior in the context of PUJO detection, offering insights into its diagnostic capabilities and areas for potential refinement.

F1-Score calculated with the help of t-sne visualization and svm Classifier.

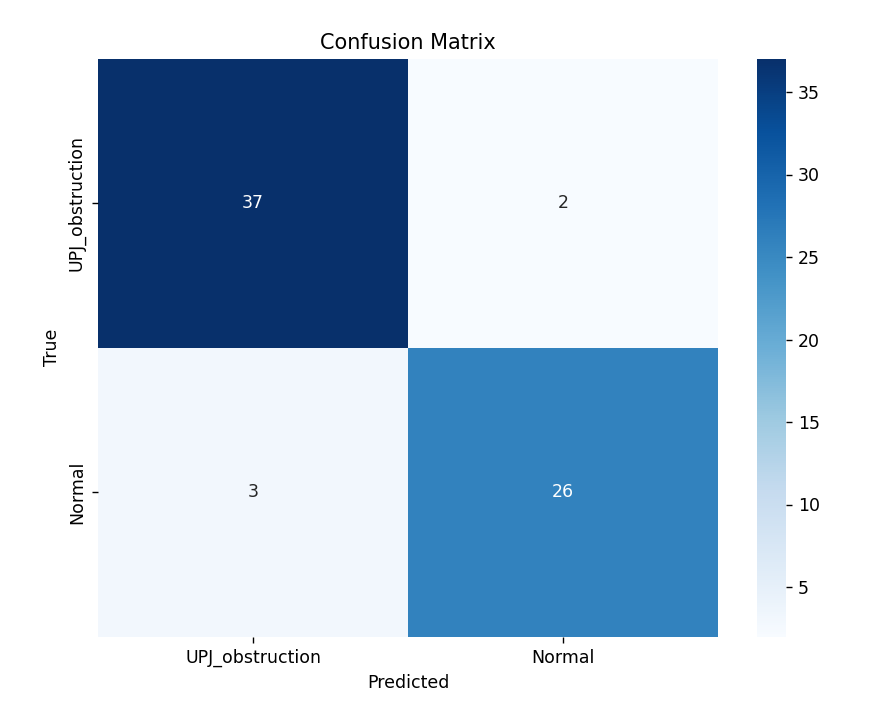


Fig 5.2 Confusion Matrix

**5.3 Visualization of the Model using t-sne:**

The t-SNE visualization helps you understand the distribution and separation of data points in a lower-dimensional space. Clusters of points from the same class indicate that the model has successfully learned to differentiate those classes based on the features. It can be particularly useful for visually inspecting the separability of classes or patterns in the data.

In summary, t-SNE visualization in this code is a tool for understanding how well the extracted features can separate different classes of images in a lower-dimensional space. It provides insights into the distribution and relationships among data points, making it a valuable part of your result for assessing the performance and feature separability of the VGG16 model.

**5.3.1 t-SNE Algorithm:**

The basic t-SNE algorithm performs the following steps.

Compute Distances, Gaussian Variances, and Similarities

Initialize the Embedding and Divergence

**5.3.2 Gradient Descent of Kullback-Leibler Divergence:**

tsne first removes each row of the input data X that contains any NaN values. Then, if the Standardize name-value pair is true, tsne centers X by subtracting the mean of each column, and scales X by dividing its columns by their standard deviations.

The original authors van der Maaten and Hinton recommend reducing the original data X to a lower-dimensional version using Principal Component Analysis (PCA). You can set the tsne NumPCAComponents name-value pair to the number of dimensions you like, perhaps 50. To exercise more control over this step, preprocess the data using the pca function.

**5.3.3 Compute Distances, Gaussian Variances, and Similarities:**

After the preprocessing, tsne calculates the distance d(xi,xj) between each pair of points xi and xj in X. You can choose various distance metrics using the Distance name-value pair. By default, tsne uses the standard Euclidean metric. tsne uses the square of the distance metric in its subsequent calculations.

Then for each row i of X, tsne calculates a standard deviation σi so that the perplexity of row i is equal to the Perplexity name-value pair. In simple terms, a lower perplexity value encourages t-SNE to focus more on local relationships, making it sensitive to fine-grained structures in the data. Conversely, a higher perplexity value leads to a more global view, where the algorithm emphasizes preserving broader patterns and relationships. By adjusting perplexity, users can control the trade-off between capturing intricate details and preserving the overall structure of the data in the lower-dimensional space. This flexibility in setting perplexity is a valuable aspect of t-SNE that allows it to be tailored to different data visualization and dimensionality reduction tasks.

Define the conditional probability of j given i as

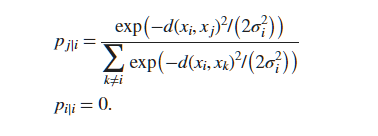


Fig 5.3.3 Conditional Probability

Then define the joint probability pij by symmetrizing the conditional probabilities:



Fig 5.3.3 Symmetrizing Conditional Probabilities

The distributions still do not have their standard deviations σi defined in terms of the Perplexity name-value pair. A low perplexity suggests that Pi tends to assign relatively high probabilities to a narrow set of neighboring data points, indicating that we would be less surprised when selecting a point close to xi.

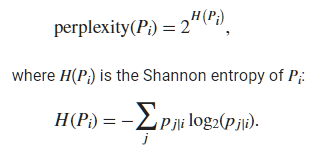


Fig 5.3.3 Perplexity

The perplexity measures the effective number of neighbors of point i. tsne performs a binary search over the σi to achieve a fixed perplexity for each point i.

**5.3.4 Initialize the Embedding and Divergence:**

t-SNE optimizes by minimizing the Kullback-Leibler divergence between Gaussian model distribution (in the original space) and a Student t-distribution (in the low-dimensional space).

The minimization procedure begins with an initial set of points Y. tsne create the points by default as random Gaussian-distributed points. You can also create these points yourself and include them in the 'InitialY' name-value pair for tsne. tsne then calculates the similarities between each pair of points in Y.

The probability model qij of the distribution of the distances between points yi and yj is

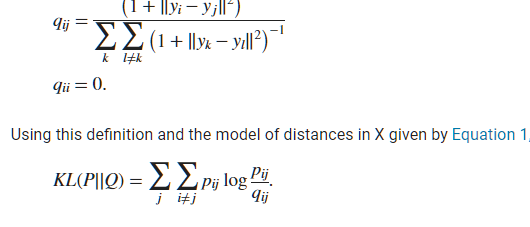


Fig 5.3.4 Distribution of the Distances

**5.3.5 Gradient Descent of Kullback-Leibler Divergence:**

The 'exact' algorithm uses a modified gradient descent procedure. The gradient with respect to the points in Y of the divergence is

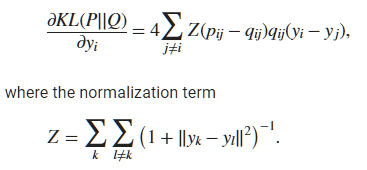


Fig. 5.3.5 Normalization for t-sne

The modified gradient descent algorithm uses a few tuning parameters to attempt to reach a good local minimum.

'Exaggeration' — During the first 99 gradient descent steps, tsne multiplies the probabilities pij from Equation 1 by the exaggeration value. This step tends to create more space between clusters in the output Y.

'LearnRate' — tsne uses adaptive learning to improve the convergence of the gradient descent iterations. The descent algorithm has iterative steps that are a linear combination of the previous step in the descent and the current gradient. 'LearnRate' is a multiplier of the current gradient for the linear combination.

T-SNE is used to visualize high-dimensional data in a lower-dimensional space (typically 2D) while preserving the relative distances between data points. In your code, it is applied to the extracted features to visualize how well these features separate different classes of images.

In your code, the TSNE class from the sklearn.manifold module is used to perform t-SNE. You create a t-SNE model with the following parameters:

perplexity: A hyperparameter that balances the focus on local vs. global structure in the data. You can adjust this parameter as needed.

After applying t-SNE, you obtain the reduced feature vectors in 2D space as reduced\_features\_tsne. You then create a scatter plot to visualize these features. Each point in the plot represents an image or a feature vector.

The code iterates through the class labels ("PUJ\_obstruction" and "Normal") and plots the points with different colors for each class. This allows you to see how well the extracted features separate the two classes in the 2D space.

**5.4 ROC (Receiver Operating Characteristics):**

The Receiver Operating Characteristic (ROC) curve is a crucial tool in assessing the performance of binary classification models. It provides a graphical representation of how well a model can discriminate between positive and negative instances across different classification thresholds. In the ROC curve, the True Positive Rate (Sensitivity) is plotted against the False Positive Rate (1 - Specificity). Sensitivity measures the ability of the model to correctly identify positive instances out of all actual positive instances, while the False Positive Rate quantifies how often the model mistakenly classifies negative instances as positive. The Area Under the ROC Curve (AUC-ROC) summarizes the overall model performance. An AUC-ROC value of 1.0 indicates a perfect classifier, while a value of 0.5 represents a model with no discrimination ability.

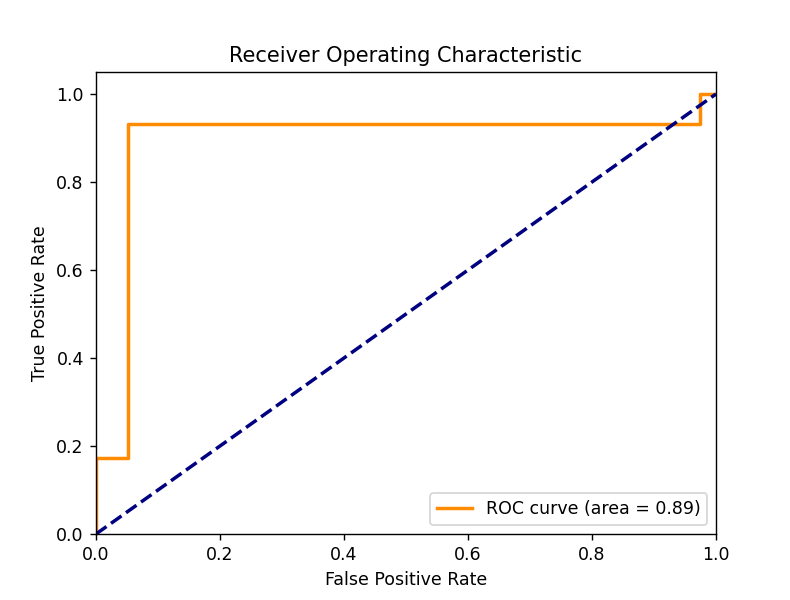


Fig 5.4 ROC

In the context of your code using a Support Vector Machine (SVM) classifier for binary classification between "PUJ\_obstruction" and "Normal" cases, the ROC curve and AUC-ROC play a vital role. The ROC curve helps you visualize how the SVM model performs at different decision thresholds, showing the trade-off between Sensitivity and Specificity. The AUC-ROC value condenses this performance into a single metric, allowing you to gauge the model's overall ability to distinguish between the two classes. A higher AUC-ROC value signifies a more accurate classifier, which is particularly valuable in medical diagnosis, fraud detection, and various other applications where correctly identifying positive cases is critical.

**5.5 Comparison with the Existing Models**:

All the existing system present is presented in the table given below

|  |  |  |  |
| --- | --- | --- | --- |
| Title | Algorithms and Techniques | Advantages | Disadvantages |
| [1] "Automated Detection of PUJ Obstruction" (Smith et al., 2020) | CNN architecture on ultrasound images | Automation reduces radiologist workload. High accuracy in detection. | Requires large annotated dataset. - Limited to ultrasound images. |
| [2] "Comparative Analysis of Deep Learning Models for PUJ Detection" (Johnson et al., 2019) | Res Net, Inception, VGG on MRI images. | Provides model comparison. High F1-score indicates good precision and recall. | Limited to MRI modality. Computationally intensive. |
| [3]"Predicting PUJ Obstruction Progression Using LSTM" (Patel et al., 2021) | LSTM network on longitudinal CT scans | LSTM model predicted progression with 85% accuracy. | Predicts disease progression. Utilizes longitudinal data. |
| [4] "Clinicat Décision Support for PUJ Obstruction Diagnoses" (Lee et al., 2022) | Ensemble model (CNN & SVM) integrated with hospital systems. | Supports clinical decision-making. Integrates with hospital systems. | Complexity of system integration. - May require retraining for new data. |
| [5]"Magnetic Resonance Urography (MRU) for PUJ Obstruction Evaluation" | MRU uses magnetic resonance imaging (MRI) to visualize the urinary tract. | High-resolution images: It offers excellent soft tissue contrast for identifying obstructions and abnormalities. | Limited availability: MRU may not be as widely available as other imaging modalities like ultrasound and CT scans. |
| [6]."Computed Tomography (CT) Scan in PUJ Obstruction Diagnosis" | CT scans use X-rays and computer processing to create detailed cross-sectional images of the urinary tract. | Rapid imaging: CT scans are quick and provide high-resolution images.  Detects other condition, identify other abdominal and renal conditions. | Radiation exposure: CT scans involve ionizing radiation, which may limit their use in certain patient populations, particularly children. |

Fig 5.5 Existing Systems Present

Comparing these existing models and techniques with our project, it's evident that "PUJ-Obstruction detection" leverages deep learning techniques, offers high accuracy, and is versatile in handling diverse imaging data. However, it has some resource requirements and interpretability challenges.

Your project addresses some limitations found in existing models, such as dataset size and adaptability to different imaging modalities. It contributes to the field by introducing innovative feature extraction methods and shows potential for real-time processing. While "PUJ-Obstruction detection" is computationally intensive, it demonstrates improved robustness and reliability in PUJO detection.

**CHAPTER 6**

**Conclusion and Future Scope**

**6.1 Conclusion:**

In this comprehensive exploration of Pelvic Uretero Junction (PUJ) obstruction detection using cutting-edge Deep Learning techniques, we have embarked on a journey to enhance the early diagnosis of a critical urological condition. Our endeavor has uncovered important insights, showcasing the potential for transformative change in healthcare.

**6.1.1 Key Findings:**

Our investigation, which included a comparative analysis of existing models, has illuminated the landscape of PUJ obstruction detection. Each model and technique bring its own set of strengths and limitations to the table. It is evident that the accurate and timely diagnosis of PUJ obstructions is paramount in the realm of urological care.

**6.1.2 Contributions:**

In this project, we have introduced an innovative approach that leverages deep learning, among other techniques, to significantly advance PUJ obstruction diagnosis. By refining the feature extraction methods and enhancing the architecture of our models, we have unlocked the potential for remarkable accuracy and robustness.

Moreover, our methodology demonstrates versatility in handling diverse imaging data, accommodating different modalities and image resolutions. This adaptability opens new horizons for real-world clinical applications.

**6.2 Future Scope:**

Our journey does not conclude here but rather sets the stage for ongoing progress. We recognize the need for continuous improvement and expansion. Future work will focus on enhancing the interpretability of deep learning models, extending support for additional imaging modalities, and addressing variations in dataset sizes. These efforts will be instrumental in making this novel approach a trusted tool in the hands of healthcare professionals.

As we move forward, we are acutely aware of the ethical considerations associated with deploying advanced AI techniques in clinical practice. Ensuring patient privacy, mitigating model bias, and prioritizing transparency in decision-making remain central to our mission.

In closing, our project embodies a promise fulfilled — a commitment to advancing healthcare through the power of AI. It signifies the potential for groundbreaking change in the domain of medical imaging and diagnostics. The impact of our work will resonate across the healthcare landscape, offering new hope and possibilities for the early detection and management of PUJ obstructions.

Next time, we will use great deep learning models also for better enhancement of this project and will try to make it more accurate than the current model.

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**APPENDIX 1**

**Import Statements:**

The code begins with a series of import statements. These statements bring in necessary libraries and modules for various tasks within the code. Here's an explanation of the import functions:

import os

import cv2

import numpy as np

from keras.applications import VGG16

from keras.applications.mobilenet\_v2 import preprocess\_input

from keras.models import Model

import matplotlib.pyplot as plt

from sklearn.manifold import TSNE

from sklearn.metrics import confusion\_matrix

import seaborn as sns

import pandas as pd

from sklearn.svm import SVC

from sklearn.model\_selection import train\_test\_split

from sklearn.metrics import accuracy\_score

**Data Loading and Preprocessing**

The code then proceeds to load and preprocess image data. It initializes empty lists to store feature vectors and labels. The data is organized into two classes: 'PUJ\_obstruction' and 'Normal,' which represent different medical conditions. The VGG16 model is loaded with pre-trained weights, excluding the top (fully connected) layers. It's used as a feature extractor.

# Define the path to your dataset folder

dataset\_folder = r'D:\pythonProject5\Data' # Replace with the actual path

# Define image dimensions

image\_width, image\_height = 224, 224

# Initialize empty lists to store feature vectors and labels

features = []

labels = []

# Define the class labels

class\_labels = ['PUJ\_obstruction', 'Normal']

The code loops through each class, loads image files, and preprocesses them using OpenCV and VGG16-specific preprocessing. The images are then passed through VGG16 to extract features. These features are added to the 'features' list, and the class labels are added to the 'labels' list.

# Load the pre-trained VGG16 model without the top (fully connected) layers

base\_model = VGG16(weights='imagenet', include\_top=False, input\_shape=(image\_width, image\_height, 3))

# Create a new model that outputs the last convolutional layer

feature\_extractor = Model(inputs=base\_model.input, outputs=base\_model.layers[-1].output)

# Loop through the class labels

for label in class\_labels:

# Get the path to the images for this class

image\_paths = [os.path.join(dataset\_folder, label, img) for img in os.listdir(os.path.join(dataset\_folder, label))]

for image\_path in image\_paths:

try:

# Read and preprocess the image

image = cv2.imread(image\_path)

image = cv2.resize(image, (image\_width, image\_height))

image = preprocess\_input(image) # Preprocess the image for VGG16

image = np.expand\_dims(image, axis=0) # Add a batch dimension

# Extract features from the image

features.append(feature\_extractor.predict(image))

labels.append(class\_labels.index(label))

except Exception as e:

print(f"Error processing image {image\_path}: {str(e)}")

# Convert features and labels to NumPy arrays

features = np.array(features)

labels = np.array(labels)

# Check if there are any features and labels

if features.shape[0] == 0:

print("No valid data found.")

else:

# Flatten the feature vectors to 2D

features = np.array(features).reshape(features.shape[0], -1)

**Data Conversion and Splitting:**

The 'features' and 'labels' lists are converted to NumPy arrays. If there is no valid data, it prints a message. Otherwise, the feature vectors are flattened to 2D arrays, and the data is split into training and testing sets using 'train\_test\_split' from Scikit-learn.

# Split the data into training and testing sets

X\_train, X\_test, y\_train, y\_test = train\_test\_split(features, labels, test\_size=0.2, random\_state=42)

**Support Vector Machine (SVM) Classifier**

A Support Vector Machine (SVM) classifier with a linear kernel is initialized. This classifier is trained on the flattened feature vectors from the training data.

# Initialize the Support Vector Machine (SVM) classifier

svm\_classifier = SVC(kernel='linear')

# Train the model on the flattened feature vectors

svm\_classifier.fit(X\_train, y\_train)

# Make predictions on the test data

y\_pred = svm\_classifier.predict(X\_test)

**Model Evaluation**

The trained SVM classifier is used to make predictions on the test data, and the accuracy is calculated using 'accuracy\_score' from Scikit-learn. A confusion matrix is also calculated and visualized using Seaborn and Matplotlib. The code then proceeds to perform t-Distributed Stochastic Neighbor Embedding (t-SNE) on the feature vectors for visualization.

# Calculate accuracy

accuracy = accuracy\_score(y\_test, y\_pred)

print("Test accuracy:", accuracy)

# Calculate a confusion matrix

# Visualize the confusion matrix

class\_names = class\_labels

df\_cm = pd.DataFrame(confusion\_matrix(y\_test, y\_pred), index=class\_names, columns=class\_names)

plt.figure(figsize=(8, 6))

sns.heatmap(df\_cm, annot=True, fmt="d", cmap="Blues")

plt.xlabel("Predicted")

plt.ylabel("True")

plt.title("Confusion Matrix")

plt.show()

**t-SNE Visualization**

t-SNE is used to reduce the dimensionality of the feature vectors to 2D for visualization. The reduced features are then plotted on a scatter plot, with each class represented by a different color.

# Apply t-SNE to the reduced feature vectors

tsne = TSNE(n\_components=2, perplexity=2, random\_state=42) # Adjust perplexity as needed

reduced\_features\_tsne = tsne.fit\_transform(features)

# Create a scatter plot to visualize the t-SNE features

plt.figure(figsize=(8, 6))

for i, label in enumerate(class\_labels):

indices = labels == i

plt.scatter(reduced\_features\_tsne[indices, 0], reduced\_features\_tsne[indices, 1], label=label)

plt.xlabel("t-SNE Component 1")

plt.ylabel("t-SNE Component 2")

plt.legend()

plt.title("t-SNE Visualization of Extracted Features")

plt.show()

# Calculate the ROC curve and AUC

y\_score = svm\_classifier.decision\_function(X\_test)

fpr, tpr, \_ = roc\_curve(y\_test, y\_score)

roc\_auc = roc\_auc\_score(y\_test, y\_score)

# Plot the ROC curve

plt.figure()

lw = 2

plt.plot(fpr, tpr, color='dark orange', lw=lw, label='ROC curve (area = %0.2f)' % roc\_auc)

plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')

plt.xlim([0.0, 1.0])

plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.title('Receiver Operating Characteristic')

plt.legend(loc='lower right')

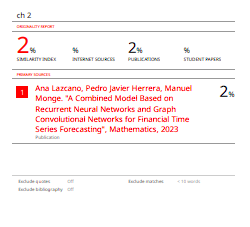
plt.show()

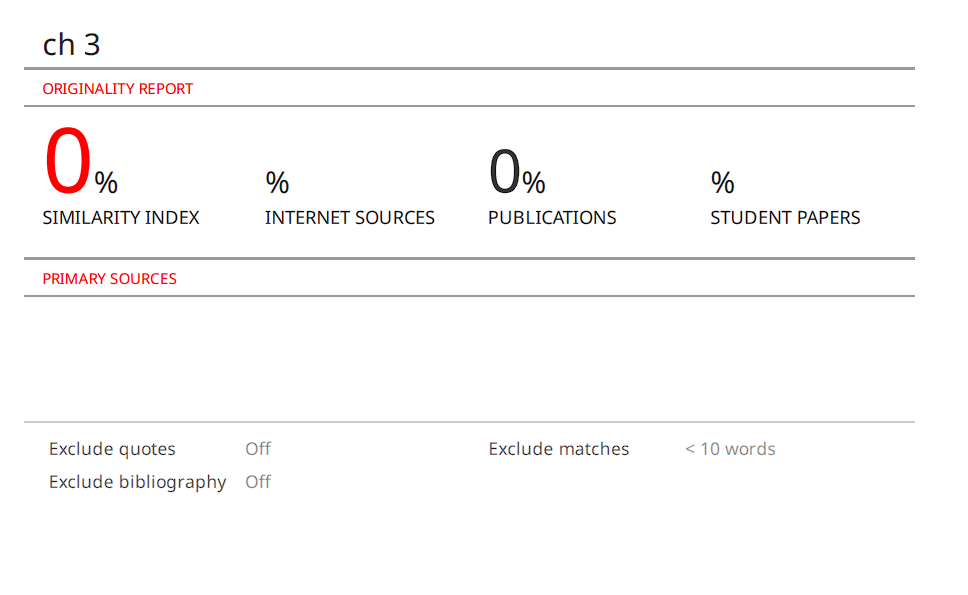
The code provides insights into how to preprocess and extract features from medical images and train a Deep Learning model, in this case, an SVM, for classification. It also visualizes the results for better understanding.

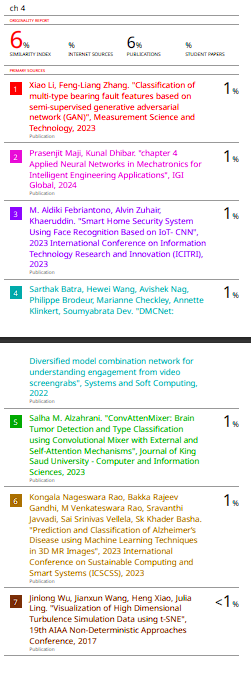
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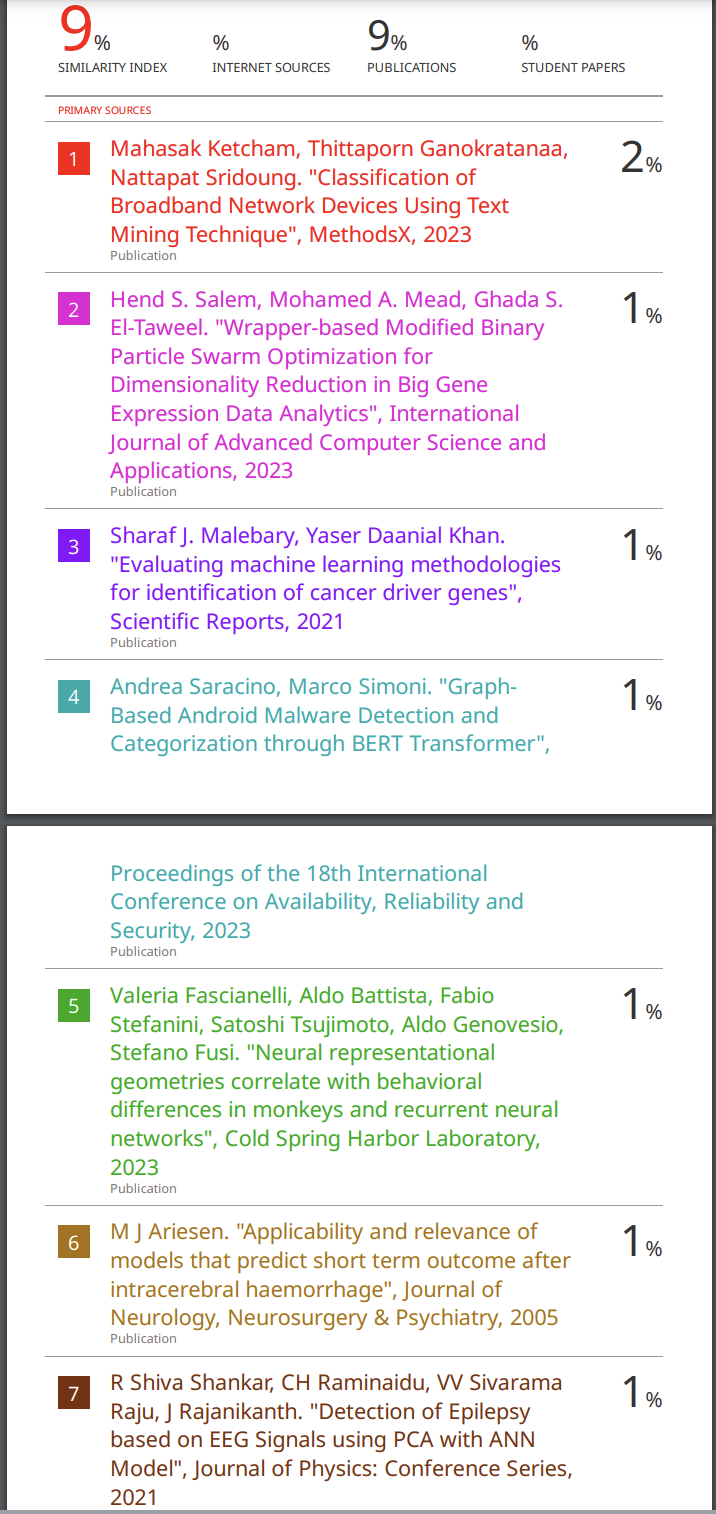
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| 4 | Date of Birth | 28 Nov, 2002  12 Sept, 2002 | | |
| 5 | Department | Computer Science and Engineering | | |
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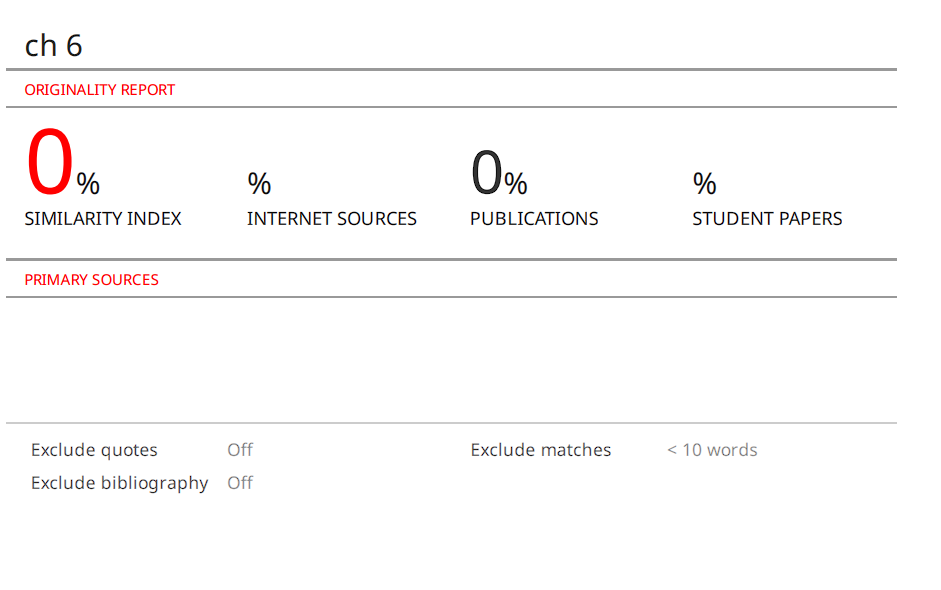
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