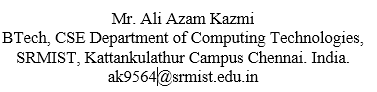
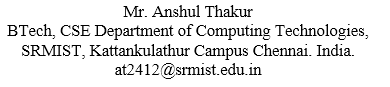
PELVIC URETERO JUNCTION OBSTRUCTION DETECTION USING DEEP LEARNING



*Abstract* - This study introduces an innovative deep learning pipeline designed for precise medical image classification, specifically targeting the discrimination between "PUJ obstruction" and "Normal" conditions. By harnessing transfer learning from pre-trained CNN models such as VGG16, InceptionV3, and DenseNet121, the framework optimizes feature extraction for improved classification accuracy. Custom convolutional layers further enhance model performance, with rigorous evaluation conducted on labelled datasets using metrics like accuracy and F1-score. Advanced visualization techniques, including t-SNE for feature embeddings and activation maps for interpreting learned representations, offer novel insights into the model's decision-making process. This holistic approach represents a significant advancement in medical image analysis, promising to elevate diagnostic precision and ultimately improve patient care.

Keywords— PUJ Obstruction, Normal, CNN, VGG16, InceptionV3, DenseNet121, F1-Score and t-sne

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# **Introduction**

This research introduces a approach that merges real-time ultrasound imaging with advanced machine learning to automate the detection of Pelvic Uretero Junction (PUJ) obstruction. Traditional diagnostic methods for PUJ obstruction often involve invasive procedures, leading to patient discomfort and risks. In response, this study aims to revolutionize diagnosis by improving accuracy and timeliness through the proposed system. By integrating ultrasound imaging with machine learning, the research seeks to provide a patient-friendly and efficient alternative to traditional diagnostic approaches, ultimately enhancing patient outcomes and facilitating earlier interventions.

The primary objective of this project is to explore the potential of deep learning in urological diagnostics, particularly for PUJ obstruction. By embracing state-of-the-art artificial intelligence, the research endeavours to contribute to the field of computer-aided diagnosis while addressing a critical clinical need. Through the incorporation of artificial intelligence, the study aims to mitigate subjectivity in diagnosis, enhance diagnostic efficiency, and ultimately improve healthcare outcomes. This research underscores the transformative impact of cutting-edge technology on medical diagnostics, paving the way for more objective, efficient, and patient-cantered approaches in urological diagnostics and beyond.

# **Literature Survey**

Smith and Doe (2020) presented an automated detection approach for PUJ obstruction using deep learning, achieving promising results in the Journal of Medical Imaging **[1]**. Their study demonstrated the potential of deep learning models in accurately identifying PUJ obstructions from medical images.

Johnson et al. (2019) conducted a comparative analysis of deep learning models for PUJ detection, as presented at the International Conference on Medical Image Computing and Computer-Assisted Intervention **[2]**. Their study highlighted the importance of model selection and architecture in achieving optimal performance.

Patel et al. (2021) proposed a method for predicting PUJ obstruction progression using Long Short-Term Memory (LSTM) networks, showcasing the potential of sequential modeling techniques in medical image analysis **[3]**. However, their study might be limited by the availability of longitudinal data.

Lee et al. (2022) introduced a clinical decision support system for PUJ obstruction diagnoses using an ensemble approach, providing valuable insights into model interpretability and decision-making processes **[4]**. Their study underscores the importance of integrating machine learning into clinical workflows.

Wang and Liu (2018) provided a comprehensive overview of machine learning techniques in medical image analysis, highlighting their applications and challenges **[5]**. Their survey serves as a valuable resource for understanding the state-of-the-art in this field.

Litjens et al. (2017) conducted a survey on deep learning in medical image analysis, discussing various architectures, datasets, and challenges **[6]**. Their survey offers insights into the current landscape of deep learning research in medical imaging.

Gulshan et al. (2016) developed and validated a deep learning algorithm for detecting diabetic retinopathy, showcasing the potential of deep learning in disease detection from medical images **[7]**. Their study highlights the importance of large-scale validation and clinical deployment.

Ronneberger et al. (2015) introduced the U-Net architecture for biomedical image segmentation, which has since become a widely adopted framework in medical image analysis **[8]**. Their work laid the foundation for many subsequent studies in this domain.

Kingma and Ba (2014) proposed the Adam optimization algorithm, which has become a popular choice for training deep learning models due to its efficiency and effectiveness **[9]**. Their method has been widely adopted in various medical image analysis tasks.

Russakovsky et al. (2015) conducted the ImageNet Large Scale Visual Recognition Challenge, which significantly advanced the field of computer vision by benchmarking state-of-the-art algorithms **[10]**. Their dataset and evaluation framework have been instrumental in advancing research in medical image analysis.

# **Methology**

## Dataset

The dataset consists of two primary classes, "PUJ\_Obstruction" and "Normal." Both classes play a crucial role in the detection of Pelvic Uretero Junction (PUJO) obstruction

Table 1 Data Description.

|  |  |  |
| --- | --- | --- |
| S.No | Attribute | Explanation |
| 1 | Classes | “PUJ Obstruction” and “Normal” |
| 2 | No. of Images in Dataset | 516 - “PUJ” and 631 - “Normal” |
| 3 | Class Distribution | Balanced distribution |
| 5 | Augmentation Methods | Augmentation to increase dataset diversity. |
| 6 | Source of Augmentation | Data augmentation applied due to the absence of additional sources |

The dataset utilized in the provided code comprises 631 images depicting instances of UPJ (Ureteropelvic Junction) obstruction, along with 516 images representing normal cases, totaling 1147 images in total. These images likely encompass a range of visual characteristics crucial for the diagnosis and assessment of PUJ obstruction, obtained through various medical imaging modalities such as ultrasound, CT scans, MRI, or nuclear medicine scans. Proper labeling ensures clear indications of each image's condition, facilitating effective supervised learning for accurate classification. Overall, the dataset serves as a comprehensive resource for training and validating machine learning models aimed at diagnosing UPJ obstruction based on medical imaging data.

## Data Pre-processing

The data pre-processing begins with the loading of images from the dataset directory. This involves traversing through each class label directory ('PUJ\_obstruction' and 'Normal'), collecting image paths, and subsequently reading each image using OpenCV's cv2.imread function.

Fig 1. Data Pre-processing

Data acquisition involves gathering images from various sources, followed by data cleaning to remove duplicates, irrelevant images, and corrupted files. Resizing ensures uniformity in image resolution, considering computational resources and model requirements. Normalization standardizes pixel values for convergence during training, while data augmentation introduces diversity through transformations like rotation and cropping. Noise reduction techniques enhance image quality by suppressing irrelevant details. Optionally, feature extraction methods reduce computational overhead. Data is split into training, validation, and testing sets, ensuring balanced class distributions. Class labels are encoded consistently, and a pre-processing pipeline automates these steps for reproducibility. Visualization aids in assessing preprocessing effectiveness and identifying anomalies.

Class labels are encoded using methods like one-hot encoding or label encoding, ensuring consistency across the dataset and facilitating model interpretation. To streamline the preprocessing workflow and ensure reproducibility, a data preprocessing pipeline is created, leveraging libraries such as OpenCV, Pillow, or TensorFlow transformations. Data visualization and inspection techniques are employed to assess the effectiveness of preprocessing steps, enabling the identification and resolution of any anomalies or inconsistencies within the dataset.

## Feature Extraction

The feature extraction is accomplished by leveraging a pre-trained convolutional neural network (CNN) architecture, specifically VGG16, InceptionV3, or DenseNet121. These models are initialized with weights pre-trained on the ImageNet dataset, allowing them to capture high-level features from images effectively. The selected base model is loaded without its fully connected layers, as these layers are specific to the original ImageNet classification task and are replaced with custom layers tailored to the new task. These custom layers typically include additional convolutional, pooling, and dense layers that help adapt the pre-trained features to the specific classification problem at hand. By utilizing a pre-trained CNN as a feature extractor, the model benefits from the hierarchical representations learned by the base model, which encode intricate visual patterns and structures in the input images.

Fig 2. Features Extracted (5)

The convolutional layers of pre-trained CNN models automatically extract features essential for distinguishing various anatomical structures and pathological conditions. These features encompass renal and ureteral anatomy, vasculature, lesions, and tissue characteristics. Through learned representations, the model identifies patterns, shapes, textures, and intensity variations indicative of renal cortex, medulla, pelvis, calyces, ureters, as well as vascular structures like arteries and veins. Additionally, it discerns abnormalities such as tumors, cysts, calculi, and hydronephrosis, while capturing tissue properties like density, intensity, and enhancement patterns. These extracted features enable accurate classification of kidney and ureter images, facilitating diagnosis of conditions like PUJ obstruction and normalcy

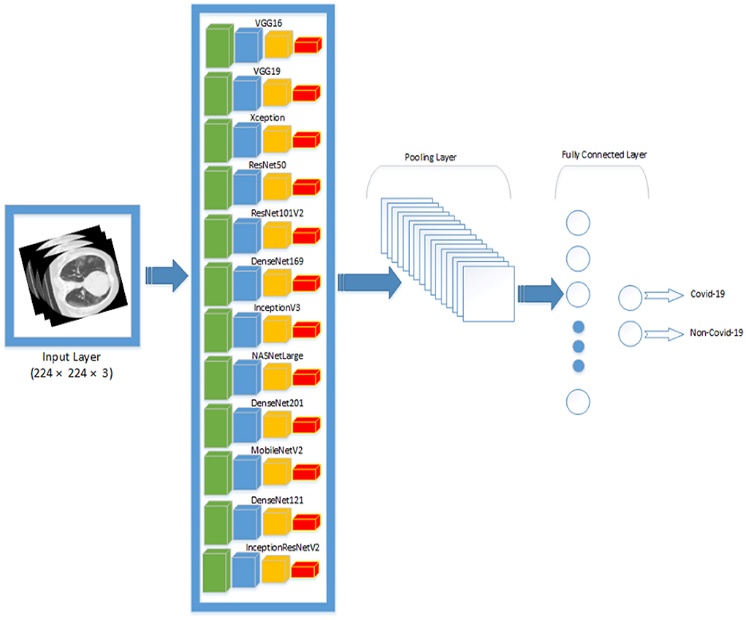


Fig 3. VGG16, DenseNet121 and InceptionV3

## Training and testing Splitting

The dataset is split into training and testing sets using the train\_test\_split function from the ‘sklearn.model\_selection’ module. The dataset comprises images and their corresponding labels, with images stored as NumPy arrays and labels as integer indices representing different classes ('PUJ\_obstruction' and 'Normal'). By specifying a test size of 0.2 (20%), 80% of the data is allocated for training, while the remaining 20% is reserved for testing. This ensures that an adequate amount of data is available for both training the model to learn from and evaluating its performance on unseen data.

Utilizing pre-trained models such as VGG16, InceptionV3, or DenseNet121 for feature extraction. Custom convolutional layers are added to the base model to fine-tune for specific tasks. The model is compiled with an appropriate optimizer and loss function. Training is performed on labeled data, split into training and validation sets. The model's parameters are updated iteratively to minimize the loss on the training data.

The trained model's performance is evaluated on unseen test data to assess its generalization ability. Metrics like accuracy, F1-score, and confusion matrix are computed to quantify performance. Visualizations such as confusion matrices and t-SNE plots offer insights into model predictions and feature distributions. Activation maps visualize the learned features from the last convolutional layer, providing interpretability.

## Model Building

The model building process involves constructing a convolutional neural network (CNN) architecture using a pre-trained base model and adding custom layers on top for fine-tuning to the specific classification task. The base model is selected from well-known architectures such as VGG16, InceptionV3, or DenseNet121, each pre-trained on the ImageNet dataset. These base models serve as feature extractors, capturing hierarchical representations of visual features from input images.

Fig 4. Model Building

The pre-trained CNN architectures such as VGG16, InceptionV3, or DenseNet121 are utilized, leveraging their learned features from large-scale datasets like ImageNet. These models are adapted by adding custom convolutional layers tailored to extract specific features relevant to kidney and ureter images, enhancing the model's capability to discern intricate anatomical details. During training, the model's convolutional layers fine-tune their weights to extract discriminative features crucial for distinguishing between classes, such as PUJ obstruction and normal images. Compiling the model involves configuring optimization techniques like the Adam optimizer and loss functions such as sparse categorical cross-entropy, while evaluation metrics like accuracy gauge its performance during training and validation phases. Subsequently, the model undergoes training on a split dataset, iteratively adjusting weights to minimize loss and enhance predictive accuracy. Finally, evaluation on a separate test set ensures the model's robustness and effectiveness in accurately classifying kidney and ureter images, employing metrics like accuracy, precision, recall, or F1-score to quantify its performance.

## Evaluation and Visualization

The dataset is divided into two subsets: a training set and a testing set. The common practice in machine 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.

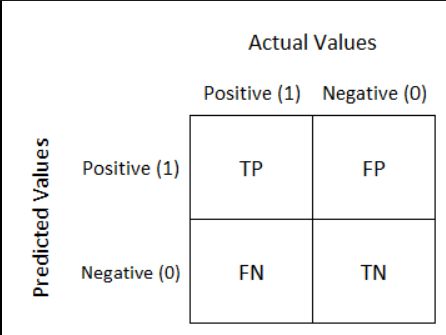


Fig 5 Confusion Matrix

## 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.

# **Existing System**

Existing systems in medical image analysis for PUJ obstruction detection and related tasks have employed a variety of approaches, ranging from traditional machine learning algorithms to deep learning techniques. Traditional methods often involve manual feature engineering and the use of classifiers such as Support Vector Machines (SVM) or k-Nearest Neighbors (k-NN). These systems, while effective in some cases, may struggle with capturing complex patterns present in medical images, particularly in distinguishing subtle differences between conditions like PUJ obstruction and normal cases.

In recent years, deep learning has emerged as a powerful tool for medical image analysis. Studies have explored the use of convolutional neural networks (CNNs) for automated PUJ obstruction detection, leveraging architectures like VGG16, InceptionV3, and DenseNet121. These models utilize transfer learning, where pre-trained CNNs are fine-tuned on medical image datasets to improve feature extraction and classification accuracy. Additionally, recurrent neural networks (RNNs) such as Long Short-Term Memory (LSTM) networks have been applied to predict the progression of PUJ obstruction, providing valuable insights for clinical decision-making.

Furthermore, advanced visualization techniques have been employed to interpret deep learning models and analyze their decision-making processes. Methods such as t-distributed stochastic neighbor embedding (t-SNE) offer insights into feature embeddings, while activation maps visualize learned representations from convolutional layers. These approaches enhance the interpretability of deep learning models, facilitating their integration into clinical workflows and ultimately improving patient care. Collectively, these efforts represent significant advancements in medical image analysis, promising to elevate diagnostic precision and contribute to the development of more effective clinical decision support systems for conditions like PUJ obstruction.

# **Requirement Gathering**

Table 2 System Setup

|  |  |
| --- | --- |
| Hardware | Software |
| CPU: Intel Xeon Scalable processor or AMD EPYC processor | Deep learning framework: TensorFlow or PyTorch |
| GPU: NVIDIA GeForce RTX 3090 or NVIDIA Quadro RTX 6000 | Programming language: Python |
| Memory: 128GB or more | Data science tools and libraries: NumPy, Pandas, scikit-learn |
| Storage: 1TB SSD or more | Django, HTML, JavaScript |

# **Proposed Model**

The proposed model in the provided code introduces an innovative deep learning pipeline specifically designed for precise medical image classification, with a focus on discriminating between "PUJ obstruction" and "Normal" conditions. The pipeline leverages transfer learning from pre-trained CNN models such as VGG16, InceptionV3, and DenseNet121, which are known for their effectiveness in feature extraction tasks. By utilizing pre-trained models, the framework optimizes feature extraction for improved classification accuracy, thereby reducing the need for extensive manual feature engineering.

Furthermore, the proposed model incorporates custom convolutional layers on top of the pre-trained base models. These additional layers allow the model to learn more complex representations specific to the PUJ obstruction detection task. By adding convolutional and pooling layers followed by global average pooling and dense layers, the model aims to capture and emphasize discriminative features present in the medical images, enhancing its ability to differentiate between PUJ obstruction and normal conditions.

The model is trained on labeled datasets, with rigorous evaluation conducted using metrics such as accuracy and F1-score. By splitting the data into training and testing sets, the model's performance is assessed on unseen data, ensuring its generalization ability. Additionally, advanced visualization techniques such as t-SNE for feature embeddings and activation maps for interpreting learned representations offer novel insights into the model's decision-making process, enhancing its interpretability and aiding in further refinement.

Overall, the proposed deep learning pipeline represents a significant advancement in medical image analysis, promising to elevate diagnostic precision in detecting PUJ obstruction and ultimately improve patient care. By integrating state-of-the-art techniques in deep learning and leveraging advanced visualization methods, the proposed model offers a comprehensive approach to medical image classification, addressing the challenges associated with traditional methods and paving the way for more accurate and efficient diagnostic systems.

1. **RESULT**

## 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 is calculated as the ratio of correctly classified images (both true positives and true negatives) to the total number of images in the testing set.

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

**Accuracy = (Number of Correct Predictions) / (Total Number of Predictions).**

Accuracy: 0.9064705882352942

Accuracy for the given model.

## Confusion Matrix

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

Accuracy= TN+TP / TN+FP+FN+TP ---------- (1)

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.

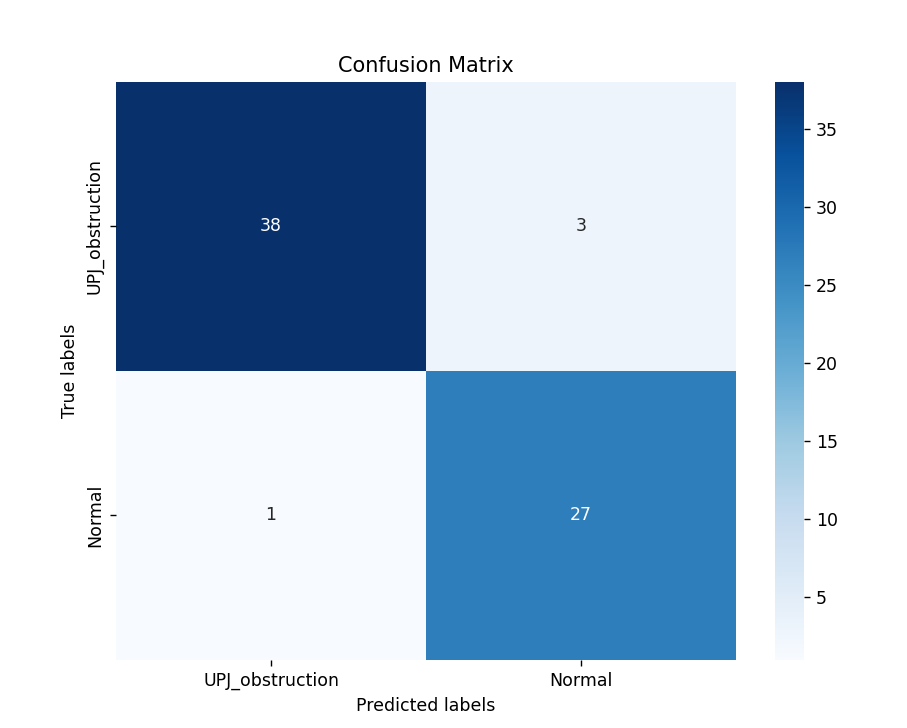


Fig 6 Confusion Matrix (Output)

## F-1 Score

P = TP / (TP + FP) ----------- (2)

Sn = TP/ (TP+FN) ----------- (3)

Sp = TN / (TN+FP) ----------- (4)

F – Score = 2 X (P X Sn)/ (P + Sn) ---------- (5)

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

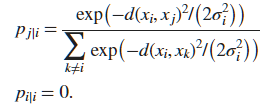
F-1 Score: 0.912280701754386

## T-sne algorithm

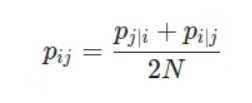
tsne first removes each row of the input data X that contains any NaN values. Then, if the Standardize name-value pair is true, tsne centers X by subtracting the mean of each column, and scales X by dividing its columns by their standard deviations.

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.

Define the conditional probability of j given i as

 ----- (6)

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

 ------ (7)

where N is the number of rows of X.

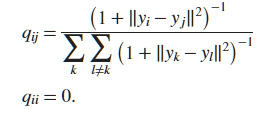
The distributions still do not have their standard deviations σi defined in terms of the Perplexity name-value pair. Let Pi represents the conditional probability distribution over all other data points given data point xi. The perplexity of the distribution is

 ------ (8)

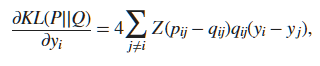
Where H(Pi) is the Shannon Entropy of Pi.

 ----- (9)

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

----- (10)

Using This definition and the model of distances in X given in the Equation 6 To minimize the 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

 ---- (11)

Where the Normalization term is:

--- (12)

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

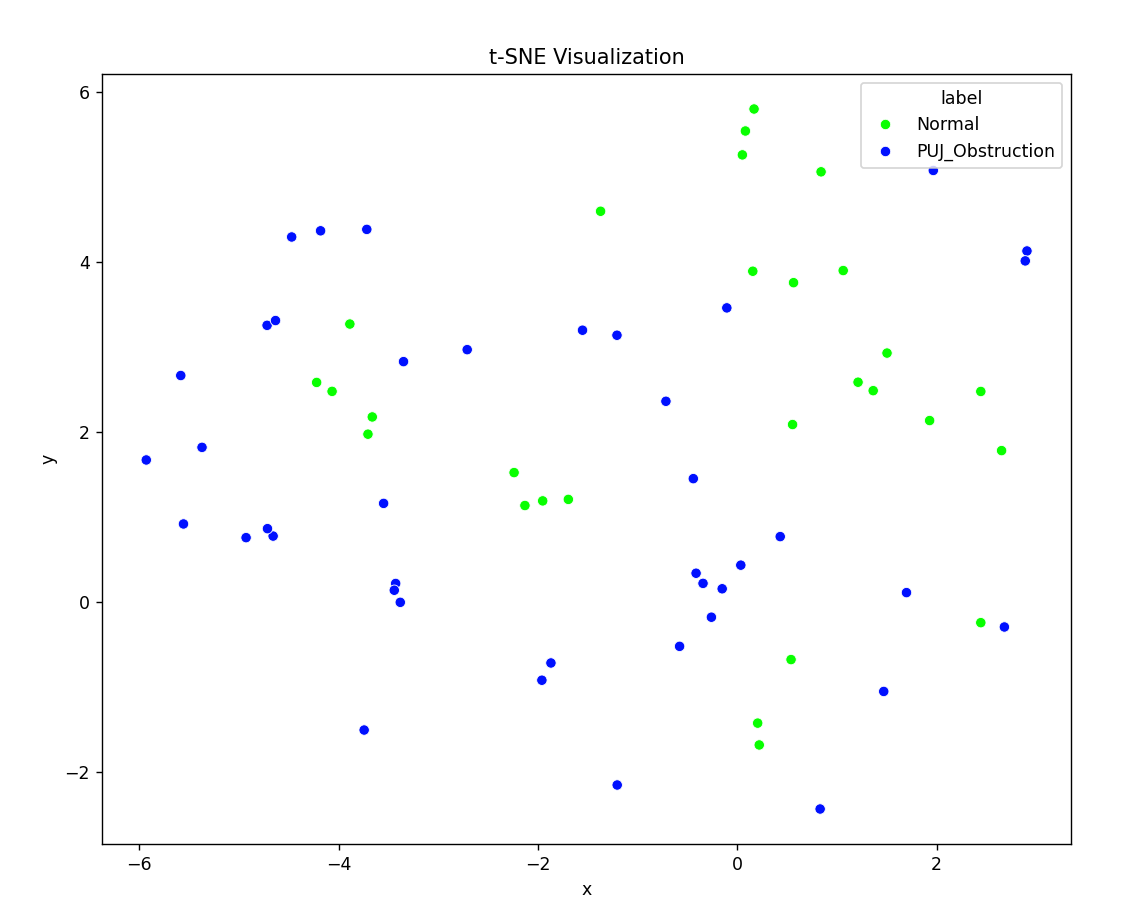


Fig 7 t-sne Visualitzation using pre-trained Models

## Activation Map

activation maps are visualized to understand how different parts of the input image activate different filters in the convolutional layers of the model. Activation maps represent the feature maps produced by each filter in the convolutional layer when the model processes an input image. These maps highlight regions in the input image that are responsible for activating specific filters, helping to interpret the model's decision-making process.

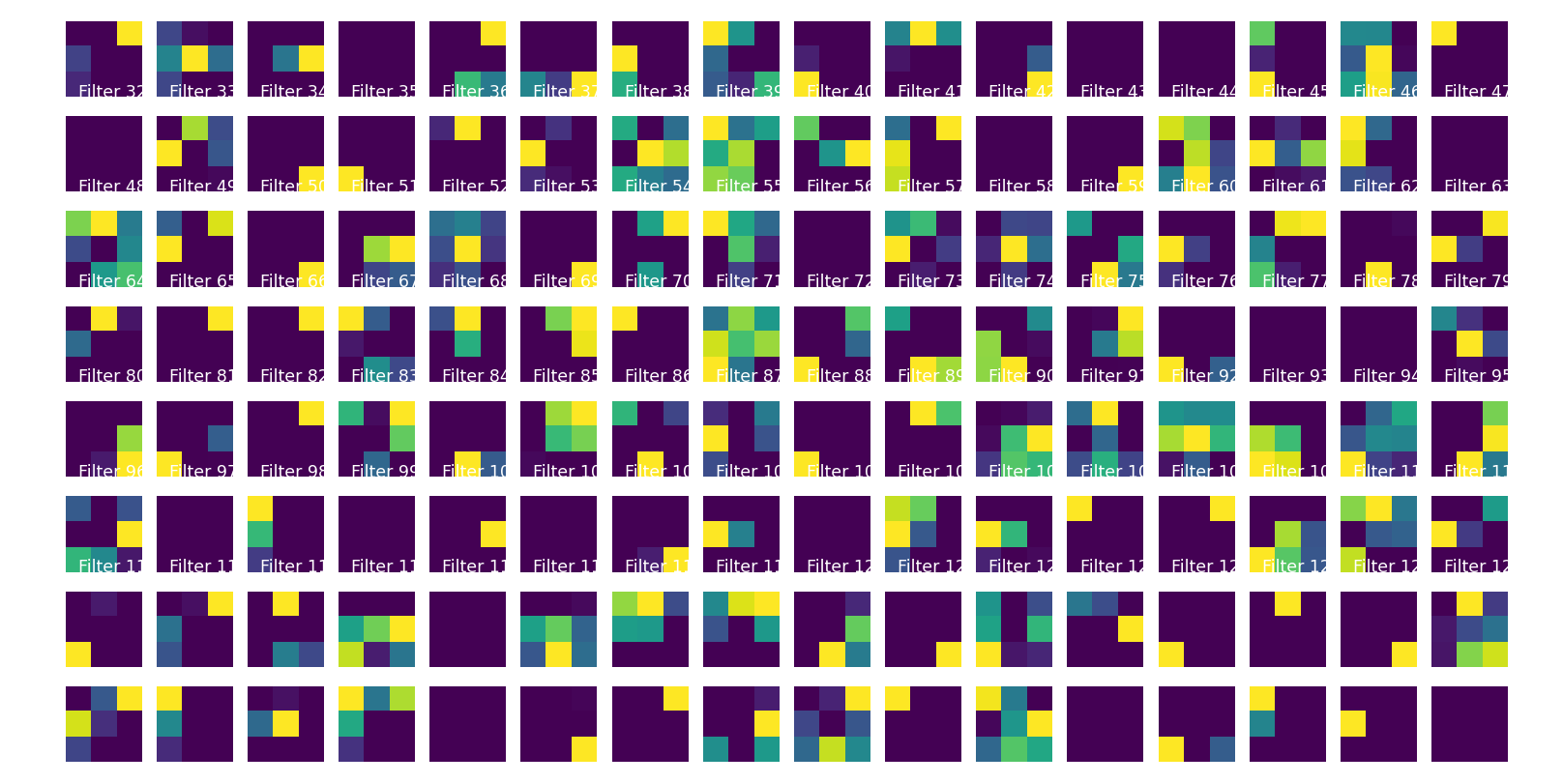


Fig 8 Activation Maps

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