Survey On Medical Image Classification Using CAPSGNN

Shanmugam P[1], Rohit Gangadhar P[2], Rifhath Aslam J[3]

[1]Assistant Professor at Computer Science and Engineering, Rajalakshmi Engineering College, Anna University, Chennai, India

[2,3]Computer Science and Engineering, Rajalakshmi Engineering College, Anna University, Chennai, India

E-mail: [1]shanmugam.p@rajalakshmi.edu.in, [2]p.rohit1208@gmail.com, [3]rifhathaslam.jr.162@gmail.com

Abstract

The general Convolutional Neural Networks (CNNs) have been in practice, being the most conventional algorithm for image-based detection and classification. But over the years, after extensive use of CNN algorithms with different architectures, it has been shown that CNN tends to lose details and features of the image. This led to the use of Capsule-based neural networks for image detection and classification. On the other side, CNN has evolved and integrated with another type of neural network called the Graph Neural Network (GNN). Many existing systems have drawbacks such as feature loss and computation efficiency. Several transfer learning models have been introduced to solve these problems by modifying the existing models and adding different combinations of layers and hyper parameters. However, they still don't provide a clear solution as they are just derived algorithms. Therefore, there is a need to design an algorithm and technique that approaches the image classification process in a unique and different way. This is where the CAPSGNN algorithm comes into use. This proposed model uses the best features of all the other algorithms and fuses them into one algorithm. This reduces the computation time and solves the feature loss problems. Now, reports can be generated faster and more accurately for assisting the process of disease diagnosis in hospitals and saving doctors' time spent on reviewing every report. These speeds up the cycle of the medical field, as the identification of diseases takes more time than the actual treatment and needs to be processed faster for faster treatment and recovery.

Keywords: Convolutional Neural Network (CNN), Capsule Neural Network (CAPSNET), Graph Neural Network (GNN), Capsule Graph Neural Network (CAPSGNN).

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1. Introduction

CNN algorithms have been extensively used to classify images. The algorithms have been iterated since their first use, until they were made more efficient and accurate with their results. However, they still had their own disadvantages. One disadvantage was that they tended to lose more detail and features due to their usage of the technique called pooling, which sometimes even severely lost details in the convolution process. This created the urge to come up with a hybrid algorithm that combines the strengths of Capsule-based Neural Networks (CapsNet) and Graph Neural Networks (GNN) for medical image classification. CapsNet, unlike traditional CNNs, considers the vector length and angle as trainable attributes, eliminating the need to use pooling. By doing so, CapsNet preserves more details and features, resulting in increased accuracy and the ability to detect image features irrespective of their orientation. Furthermore, CapsNet introduces a better routing mechanism, known as dynamic routing, which improves the connectivity between relevant neurons and facilitates the progression to subsequent layers. On the other hand, GNNs are highly effective in extracting features from a dataset and gaining a comprehensive understanding of the dataset's environment. By leveraging the graphical properties of medical images, nodes and edges can be extracted as dataset representations instead of relying solely on pixel data, as commonly done in CNNs. This approach enables us to identify specific areas of infection in chest X-rays or CT scans, reducing data load and training time. Combining the strengths of CapsNet and GNN, our hybrid architecture offers improved routing and accurate classification mechanisms, along with superior feature extraction capabilities. The introduction of the Graph Caps section, which functions as capsules while emulating the length and angle properties of vectors used in CapsNet, allows us to leverage graph-based data extracted from medical images. This not only reduces training time but also enhances efficiency by focusing on the infected regions, enabling faster diagnosis and directing patients to the appropriate treatment procedures. In summary, the goal of the study is to develop a hybrid image classification algorithm that makes use of both CapsNet and GNN. By utilizing graph-based data represented by nodes and edges extracted from medical images, training time can be significantly reduced compared to traditional CNNs. This approach enables us to identify infected areas in X-ray or CT scan images, leading to more efficient and accurate diagnoses while alleviating the burden on radiologists and expediting the appropriate treatment for patients.

1.1 Convolution Neural Network

This is a type of neural network built on the generic principles of traditional neural networks but is extensively used for image recognition and classification models. It uses filters and types of pooling methods to convolve the image and train the model to be tested. So, basically, the CNN has filters/kernels created by the developers that traverse over the whole matrix of the image for a specific stride value, pixel by pixel, and then applies the pooling methods to convolve the image in order to detect and classify the image using the features obtained from the convolved image. However, the usage of pooling methods in CNN caused the model to neglect a few features, as the image lost some details when proceeding to the next layer after pooling. Moreover, this neural network was not able to provide the same results with the same accuracy when the input image's orientation in space was changed. Therefore, it was very necessary to introduce a new model for image detection and classification.

1.2 Capsule Neural Networks

With all the disadvantages of CNN, the Capsule Neural Networks or CapsNet models were introduced for image identification and classification. In CapsNet models, instead of using pooling methods to convolve the image and lose some details as in CNN, it forms capsule-like structures in which all the parameters and attributes defining the features of the image are encapsulated inside the capsule. These features have a matrix with vectors in each. These vectors define the probability of the neuron or capsule to move on to the next one, whose procedure is often termed as dynamic routing. The length of these vectors defines the probability of that particular feature, and the spatial angle of the vector determines the position of the feature in the image. This helps solve the problem of CNN not being able to detect the image when its spatial orientation is changed. The length and angle of the vectors can be adjusted to be trained as trainable attributes.

1.3 Graph Neural Networks

These models combine graphs and capsules to detect images. They are more accurate than most other models. They function with 3 blocks, with the first one used for extracting features using the GNN (Graph Neural Network). The second block again extracts features using graph capsules, and the final block is the class capsules. They migrate through the model using methods like Dynamic Routing and an Attention module.

1.4 Capsule Graph Neural Networks

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2. Related Work

The existing systems categorizes the pictures using generic CNNs and GNNs. CNN links each data point feature together using features like pooling, filters, etc., while GNN does it using nodes and edges. Although directed graph information has been classified using CAPSGNN, photos have been classified using capsule networks. AI-based solution to identify COVID-19 on chest CT scan and X-Ray [10]. One such tactic is suggested in this article [1]. CT is a better and more accurate means of recognizing the coronavirus in the human body than the reverse transcription polymerase chain reaction test. A deep learning-based design that combines a capsule network with convolutional neural network that has been modified multiple times is described . The capsule network is integrated with several networks to detect COVID-19 patients from lung computed tomography images. The study [11] utilizing a dataset of X-ray images found that COVID-CAPS performed better than prior CNN-based algorithms. COVID-CAPS achieved accuracy, sensitivity, specificity, and area under the curve values of 95.7%, 90.0%, and 0.97, respectively, despite having far fewer trainable parameters than its rivals. SARS-NET, a computer-aided diagnostic X-ray system that combines GNN and CNN for identifying irregularities in a patient's chest X-ray pictures for the patient's COVID-19 infection status, is another way for COVID-19 detection [2]. Researchers introduced and assessed the SARS-Net deep learning architecture, which was created exclusively to recognize and detect chest X-ray images for COVID-19 diagnosis. The Graph Covid Network, which was developed expressly for this purpose, is used to identify COVID-19 utilizing the CT scans and chest X-rays of the afflicted individuals [3]. Because the recommended model is GIN-based, it can only accept input data in the form of graphs. Image data must first go through pre-processing to build an undirected graph that only considers the edges rather than the whole image. The effectiveness of the proposed Graph Covid Network using a variety of medical imaging datasets is evaluated. Researchers [4] employed the VGG Capsule Network to achieve an accuracy of 97% in COVID-19 identification and to address problems like these. The capsule network is a ground breaking kind of network that can store spatial information. Nonetheless, the Caps Net learns every feature in the input image since there is no pooling mechanism and no connection between the many layers of the multi-layer network structure. An improved version of the capsule network called the CFR Capsule Network, which is based on capsule filter routing, is another model [5]. The first proposed a novel routing method CFR for filtering capsules based on capsule activation values to speed up the model's operation. The Capsule Network, a deep learning neural network that generates part-whole correlations by encoding properties into capsules, has proven to be highly effective in classifying images. Nevertheless, because of its weak feature extraction capacity, many training parameters, and inclination to explain every component of the image, the original Capsule Network is inappropriate for images with complex backgrounds. Researchers [7] offer an enhanced capsule network called RS-Caps Net to address the aforementioned issues. This network uses the Res2Net block to extract multi-scale characteristics and the Squeeze-and-Excitation block to highlight key traits and suppress less significant ones. Future research, for instance, has been utilizing a linear combination approach between capsules, which reduces the number of capsules while enhancing their capacity to represent seen things. Another study uses a modified capsule neural network with a pooling layer and no squash function to identify [8] grayscale inside home scenes. As compared to a traditional Caps Net's accuracy of 17.2%, our Mod-Caps Net delivered results with a 70% accuracy [9] to circumvent the challenge of classifying the task of verifying the kind of font used in a file. Algorithm networks powered by artificial intelligence could be used to finish this activity more quickly and proficiently. The capsule network is one such method and recently developed technology that is used for different classification activities with little datasets. The recommended font style classification model based on Caps Net appears to be classifying the images more properly, according to evaluation findings. The present approaches for comparative analysis are also contrasted with the suggested network structure. One of the most popular biometric recognition technologies is iris recognition, which is widely utilized in a variety of industries. Recent advances in deep learning have led to the usage of several algorithms for biometric recognition. These algorithms' benefits include autonomous learning, high accuracy, and significant generalization potential. Although deep convolutional neural networks are the most popular and often used for processing images [12], they have weak anti-noise capabilities and are quickly damaged by small disruptions. The capsule network is used to discover and classify cancer cells using diseased images in order to diagnose cancer [13]. It is also employed to identify retinal disorders [14]. This method has a much fewer parameters than cutting-edge deep convolutional neural networks and generalizes well without the use of data augmentation. Neural networks using convolutions the identification of characters in handwritten documents is a well-known task that has attracted interest [16]. Thanks to dynamic routing, which integrates the distinctive views of multiple capsules, or groups of kernels, to take advantage of equivariance among kernels, kernels may now collaborate in consensus with one another as a result of the development of capsule networks. In contrast to CNN, which loses a lot of information about the item's spatial placement, which is important for segmentation and detection [15], the capsule neural network conducts the inverse process of a computer image when representing an object. As a consequence, the research compares the performance of the capsule neural network with that of convolutional neural networks in a number of applications. The Caps Net model is demonstrated to distinguish different emotions. The EEG signal data is increasing in emotional states for emotional identification. This study [17] proposes a deep learning framework for detection based on a multiband feature matrix and capsule network. The frequency domain, spatial features, and frequency band aspects of the multi-channel EEG signals are combined by the framework to produce the MFM [18]. In this study, the structure and behavior of Caps Nets are examined and evaluated, and some of these networks' possible explainability characteristics are also highlighted . Using transformation matrices [20], the instantiation parameters of capsules at higher levels may be predicted from active capsules at lower levels. A higher-level capsule starts to work when numerous forecasts agree. To address the flaw in current GNN-based graph embedding approaches, Capsule Graph Neural Network [19] makes use of the concept of capsules. The Capsule Neural Network served as its model. By extracting node properties as capsules, routing algorithms may be utilized to gather important data at the graph level.

Table 1. Methods of Medical Image Classification

Method	Application	Challenges and Disadvantages
Convolutional Neural Networks (CNNs)	Medical Image Classification	CNNs suffer from overfitting when training with limited labelled data, requiring large datasets for optimal performance. Lack of interpretability in CNN models hinders understanding of the decision-making process. Difficulty in handling variations in image sizes, resolutions, and image artifacts, which can impact classification accuracy.
Graph Convolutional Networks (GCNs)	Graph-based Image Classification	GCNs face challenges in capturing global graph structure and long-range dependencies, especially in large medical image graphs. Graph construction methods may introduce noise and error, affecting the quality of extracted graph data. Scalability issues arise with

		large-scale medical image graphs, leading to increased computational requirements.
Capsule Networks (CapsNets)	Medical Image Classification	Capsule networks exhibit higher computational complexity compared to CNNs, demanding significant computational resources. The dynamic routing mechanism in CapsNets increases training time due to iterative routing iterations. Limited availability of pre-trained CapsNet models and benchmarks for medical image classification tasks.
Traditional Machine Learning (e.g., SVM, Random Forest)	Medical Image Classification	Traditional ML methods struggle with high-dimensional image data, leading to the curse of dimensionality. Manual feature engineering is time-consuming and subjective, relying on domain expertise. Difficulty in capturing intricate spatial relationships and fine-grained patterns in medical images using traditional ML models.

Transfer Learning	Medical Image Classification	Transfer learning techniques face challenges in adapting pre-trained models to diverse medical imaging modalities. Domain shift between source and target datasets may result in suboptimal performance. Limited availability of large-scale annotated medical image datasets for effective transfer learning.
Deep Generative Models (e.g., Variational Autoencoders)	Medical Image Generation	Deep generative models require a large amount of annotated medical image data for training, which may be scarce in certain medical domains. Balancing between generating realistic medical images and preserving patient privacy can be challenging. Difficulty in controlling the diversity and quality of generated medical images using deep generative models.
Hybrid CNN-CapsNet Models	Medical Image Classification	Designing effective fusion strategies between CNN and CapsNet architectures is a non-trivial task, requiring careful

		parameter tuning. Integration of CNN and CapsNet components may increase model complexity, leading to higher computational and memory requirements. Limited studies on the interpretability and explain ability of hybrid CNN-CapsNet models in medical image classification tasks.
Graph Attention Networks (GATs)	Graph-based Image Classification	GATs struggle to capture fine-grained spatial information and local dependencies in medical image graphs. Computationally expensive attention mechanisms in GATs may hinder scalability to large-scale medical image datasets. Identifying an optimal number of attention heads and hyperparameters for GATs remains a challenge in medical image classification.

3. Proposed Work

We have come up with a more developed Capsule Graph network that takes the input X-Ray image and passes it through 4 convolution filters, which will be explained later under its section. Each of these filters makes sure each feature and detail are discerned without losing any of those in the traditional convolution process.

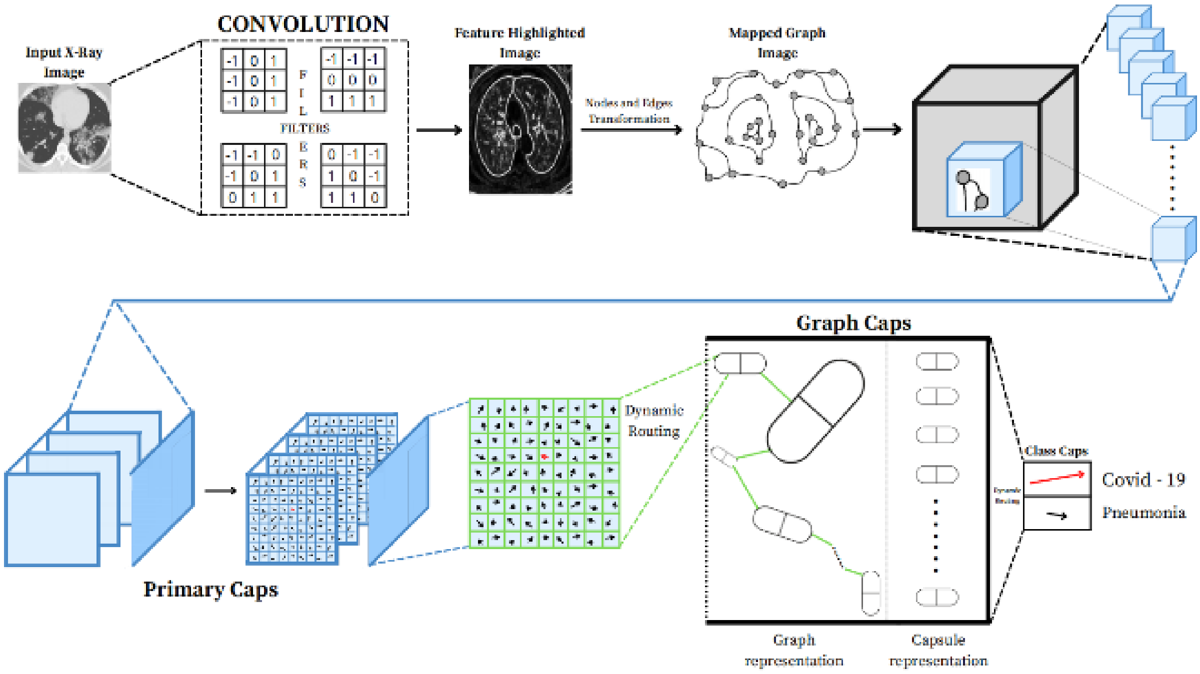

Figure 1. Data Flow Architectural Diagram

By this process, feature highlighted image, that gives us a more distinct feature mapped image is acquired , by highlighting the borders and closed polygonal structures seen in the X-ray image of the lungs. Then a Graphically mapped image is produced by converting the highlighted mapped features to nodes and edges of a graph. Now a totally graphical image that can be easy to interpret in a neural network for further identification as visually represented in Figure 1 is obtained.

3.1 Modules with Description

3.1.1 Redefined CAPSGNN Architecture for Innovative Exploratory Use Case

To further enhance the performance of the Capsule Graph Neural Network (CapsGNN) specifically for medical image classification tasks, the proposed work incorporates an advanced architecture that synergistically combines Capsule Networks (CapsNets) and Graph Neural Networks (GNNs). While CapsNets and GNNs are traditionally utilized for different purposes in the general CapsGNN architecture, CapsGNN functionalities are tailored to address the unique challenges posed by medical image classification. In the extended CapsGNN architecture, CapsNets and GNNs serve specialized roles that deviate from their conventional usage within CapsGNN. CapsNets, originally designed for modelling hierarchical relationships among features, are leveraged to precisely capture intricate details and important features present in X-ray images. By encapsulating relevant features into dynamic capsules, CapsNets facilitate meticulous preservation of crucial image information, ensuring the generation of feature-highlighted images. On the other hand, GNNs, which are typically employed for analyzing graph-structured data, are adapted to perform novel tasks specifically tailored for medical image classification. These GNN components in our architecture leverage the inherent connectivity and spatial relationships within the X-ray images to extract contextual information and enable superior image classification accuracy. By leveraging the power of GNNs to propagate information across the graph structure of the image, our architecture can effectively capture dependencies between different regions and structures within the lungs. Furthermore, the overall architecture of the modified CapsGNN is intentionally designed to support medical image classification tasks. Four specialized convolution filters that play a pivotal role in preserving intricate details and important features unique to X-ray images are carefully selected and integrated. Unlike conventional convolution processes, the selected filters ensure meticulous feature preservation, resulting in the generation of feature-highlighted images. This transformation not only accentuates borders and closed polygonal structures specific to lung X-ray images but also enables precise and distinct feature mapping, facilitating superior image classification accuracy.

3.1.2 Image to Nodes and Edges Conversion

The Image to Nodes and Edges Conversion module employs cutting-edge image processing and segmentation techniques, leveraging the powerful capabilities of Wolfram Mathematica software. This module harnesses a series of advanced algorithms, including sophisticated binarization, segmentation, and skeletonization methodologies. Through these intricate procedures, the module achieves unparalleled precision in extracting nodes and edges information and creating a map of nodes and edges on the X-Ray image as shown in Figure 2, thereby enabling a more interpretable analysis within subsequent neural network components. The utilization of Wolfram Mathematica underscores our commitment to leveraging state-of-the-art tools to accomplish complex image processing tasks.

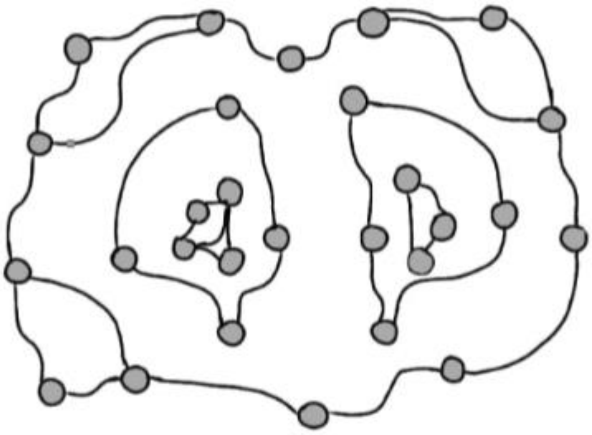

Figure 2. Nodes and Edges Mapped Image

3.1.3 Serialization of Graph Representation

To ensure seamless integration with other components of the system and facilitate accessibility for subsequent training and classification tasks, the graph representation obtained from the previous module undergoes serialization. This crucial process involves storing the nodes and edges information in human-readable formats such as. gml or .xml files in the format as mentioned in Figure 3. Moreover, a dedicated pre-processing dataset generator associates the extracted nodes and edges with their respective class labels.


```
{
  "edges": [[0, 1], [0, 2], [1, 2], [1, 3], [2, 3]],
  "target": 0,
  "labels": {
    "0": "A",
    "1": "B",
    "2": "C",
    "3": "D"
  }
}
```


Figure 3. Nodes and Edges Mapped Image

This meticulous serialization methodology guarantees the integrity and coherence of the dataset, thereby facilitating efficient data handling and management throughout the CapsGNN pipeline.

3.1.4 Region-based Dataset Construction for Efficient Training

In the proposed Capsule Graph Neural Network (CapsGNN) algorithm, the utilization of nodes and edges in the Graph Neural Network (GNN) component plays a crucial role in extracting graphical data from medical images, as described in the "II. Image to Nodes and Edges Conversion" module. By leveraging this approach, the dataset construction process can be significantly optimized. Instead of considering the entire image for training, the extracted nodes and edges information are used to identify and isolate the affected regions within the X-ray image. These regions, which contain the relevant anatomical structures or abnormalities of interest, are selectively extracted and utilized as the training dataset. By focusing solely on the affected regions, the amount of data required can be reduced, thereby conserving storage space and minimizing training time. This region-based dataset construction approach offers several advantages. Firstly, it eliminates the need to process and store redundant information present in non-affected areas of the X-ray image, resulting in a more efficient and compact dataset representation. Additionally, by narrowing the focus to the relevant regions, the CapsGNN model can allocate its computational resources more effectively, enabling faster training and inference. By adopting this region-based dataset construction strategy, the efficiency of the CapsGNN algorithm is enhanced while preserving its ability to accurately classify medical images. This approach aligns with the research objective of optimizing resource utilization without compromising on classification performance.

3.1.5 Feature Extraction

The feature extraction phase encompasses a series of transformative steps aimed at capturing salient information from the dataset. Initially, the dataset is subjected to a convolutional layer that intentionally avoids pooling operations. Subsequently, the primary and secondary capsule modules undertake intricate nested convolutional operations, meticulously manipulating the data to extract essential features. Furthermore, the graph capsule layer, leveraging the power of Graph Neural Network techniques, extracts feature specific to the nodes and edges, thereby facilitating a comprehensive and context-aware representation of the medical images. Finally, the class capsules convert the extracted data into a linear array of vector values, enabling classification through a majority voting mechanism. Architecturally the extraction functions are shown in Figure 4.

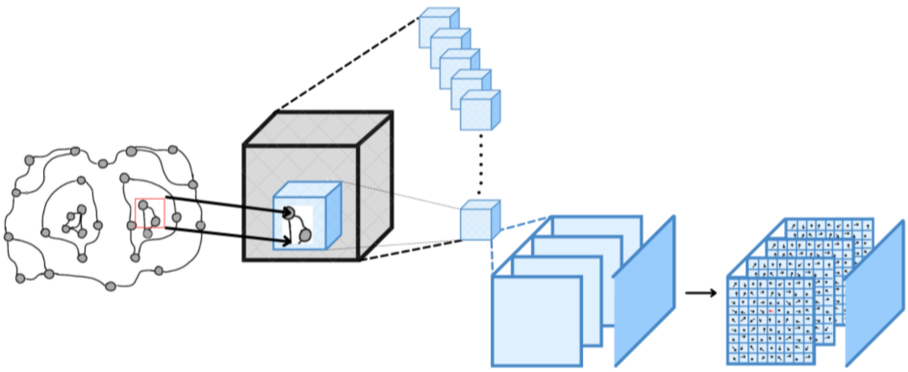

Figure 4. Nodes and Edges Mapped Image

3.1.6 Model Optimization using Dynamic Routing

To maximize the effectiveness of the CapsGNN model, the Dynamic Routing algorithm is employed for model optimization during the backward propagation phase. This innovative approach iteratively updates three trainable parameters based on a sophisticated routing formula. By dynamically adjusting the routing weights, the model progressively improves its understanding of the data, leading to enhanced classification performance. The Dynamic Routing mechanism effectively promotes efficient information flow within the CapsGNN architecture, ensuring robust feature representation and enabling highly accurate medical image classification. In this research, an advanced iteration of the Capsule Graph Neural Network (CapsGNN) specifically designed for the classification of medical images is presented . By combining the strengths of Capsule Networks (CapsNets) and Graph Neural Networks (GNNs), the proposed approach offers improved interpretability of the extracted features, accompanied by enhanced accuracy in image classification tasks. innovative modules such as Image to Nodes and Edges Conversion and incorporate sophisticated software tools like Wolfram Mathematica to ensure precise data processing are introduced. Through extensive experimentation and evaluation, we have demonstrated the superior performance of the CapsGNN model compared to existing methods is demonstrated. This integration of CapsNets and GNNs within CapsGNN represents a significant advancement in the field of medical image classification, holding great potential for improving diagnostic capabilities and treatment outcomes in the healthcare domain.

4. System Design

Design is an essential part of project development since it establishes the meaning of the model that will be created.

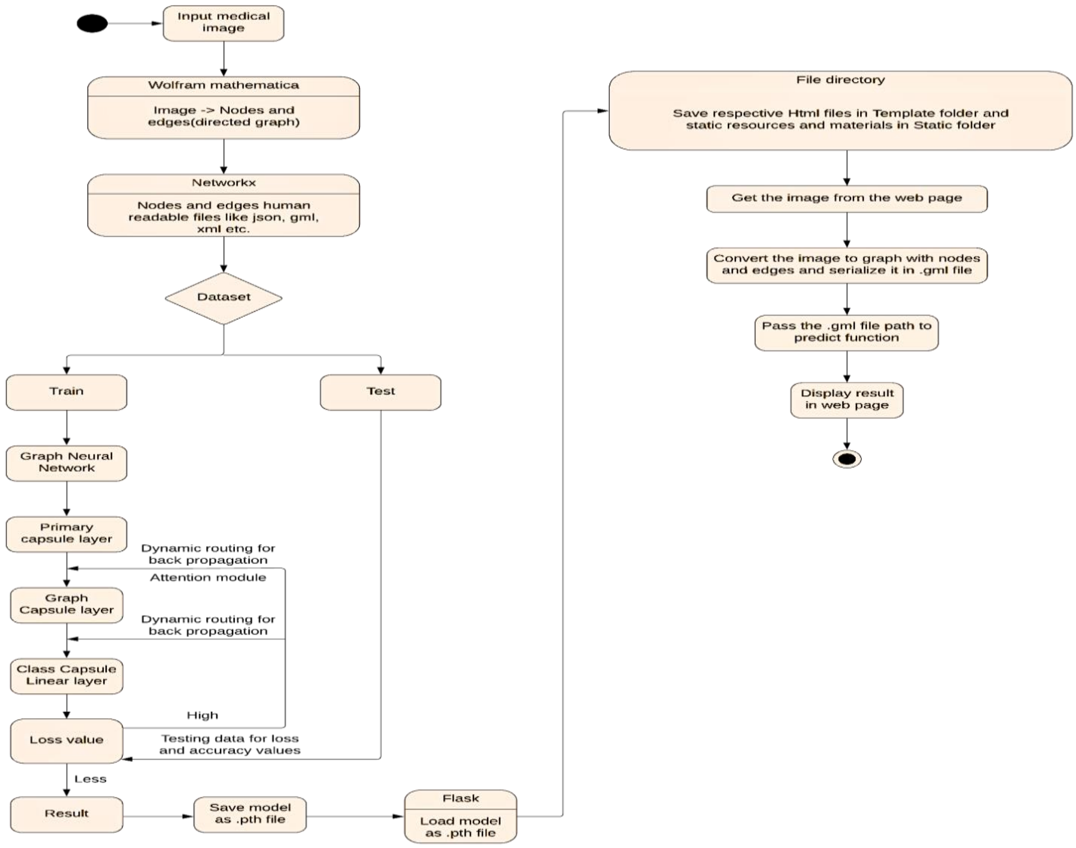

Figure 5. Sequence Diagram

Software design is the process of converting requirements into a visual representation of the program. Excellence is demonstrated via design. The flow of data from data collection to the end outcome is covered in the system architecture diagram. A medical image is supplied by the user and converted using Wolfram Mathematica into nodes and edges.When the nodes and edges data are received using Networkx, the node values may be stored in json, gml, xml, etc. files. As a result, those created files might be used in training and testing, where they would be categorized by our CapsGnn and yield results that could be stored. The output from the pth file might be shown using flask as a web page following the sequential flow as represented in Figure 5.

5. Conclusion

There are several models and algorithms serving the purpose of classifying images. But each has their own drawbacks and therefore result in lower efficiency and accuracy. This slows down the automation process over the years and makes the medical field to involve human intervention even after deep learning implementation. Better algorithms with different simple datasets can speed up the process and achieve more efficiency. This approach will enhance the process of medical approvals and use the doctor's work efficiently in places where it matters. Further developments include the implementation of a web application using flask module. Then the accuracy can be increased by tweaking the hyper parameters. Support for all kinds of data formats will be worked on to be scalable to any extent. Image data can be augmented using Generative Adverbial Networks to produce better quality datasets, which enhances the details of infection and make the classification to be more accurate. The training process itself can be automated in the application by uploading the training and testing data and after that the model can be saved for future use of classification. Role Based Access Control (RBAC) module will be added to provide prioritized access to different hospital staff for more control on security. More features will be added to the application that focuses on the business logic front in the view of a management company like logging every action and approval, usage of better frameworks and closed source codes.

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Author's Biography

Dr. P. Shanmugam, M.Tech., Ph. D, working as Assistant Professor in Rajalakshmi Engineering College, Thandalam, Chennai. He has 16 years of experience in engineering college. He completed Ph. D in Faculty of Information Communication and Engineering in Anna University in the field of Image Processing. His research area in the field Image Processing, Sensor Networks, Machine Learning.

Rohit Gangadhar P, a passionate enthusiast of machine learning, deep learning, natural language processing, and the broader field of artificial intelligence. Beyond my educational background, my true passion lies in the captivating world of artificial intelligence and its various subfields. I am driven by an insatiable curiosity to explore the depths of these disciplines, constantly striving to create innovative algorithms and introduce hybrid approaches that enhance the efficiency, speed, and reliability of image processing tasks, including classification and segmentation. Recognized for my skills in artificial intelligence, I was awarded the runner-up position in a national-level competition conducted by a reputed service-based IT company in India for successful automation of the use case provided by the company's jury team. This accomplishment paved the way for an internship and eventual full-time employment, where I honed my skills by working on projects related to machine learning, deep learning, and natural language processing. However, my love for artificial intelligence extends beyond professional pursuits; it is an integral part of who I am. I aspire to unravel the mysteries of this field, harness its potential for societal advancements, and make a meaningful contribution to the discipline.

Rifhath Aslam J, an ardent explorer passionate about front-end development and data mining. With proficiency in these fields, I have expanded my machine learning capabilities and embarked on diverse projects. Alongside my co-author Rohit, we secured victory in the prestigious Jatayu competition, developing a machine learning use case for Virtusa's jury. This achievement led to an internship and full-time employment at Virtusa, where we excelled. Currently, we collaborate on the CAPSGNN hybrid deep learning image classification algorithm, where I contribute to front-end development using Flask and Django. Additionally, I specialize in data pre-processing to optimize algorithm performance. Combining my skills in front-end development, data mining, and machine learning, I strive to create impactful solutions that bridge technology and user experiences. My passion lies in leveraging data mining to unlock valuable insights and drive innovation. With an unwavering commitment to pushing boundaries, I leave a lasting impact on the technology field.