How to Cite:
Hebbale, S., Marndi, A., Manjunatha Kumar, B. H., Mohan, B. R. ., Achyutha, P. N., & Pareek, P. K. (2022). A survey on automated medical image classification using deep learning. *International Journal of Health Sciences*, *6*(S1), 7850–7865. https://doi.org/10.53730/ijhs.v6nS1.6791

A survey on automated medical image classification using deep learning

Swaroop Hebbale
Post Graduation Student, Master of Technology, Department of Computer Science and Engineering, East West Institute of Technology, Bengaluru, Karnataka, India
Corresponding author email: swaroop.150051@gmail.com

Dr. Ashapurna Marndi
Senior Scientist, CSIR Fourth Paradigm Institute, NAL Belur Campus, Bangalore, Karnataka, India
E-mail: asha@csir4pi.in

Manjunatha Kumar B H
Professor, Department of Computer Science and Engineering, SJC Institute of Technology, Chickballapur, Karnataka, India
Email: bhm.nlp@gmail.com

B R Mohan
Professor, Department of Computer Science and Engineering, East West Institute of Technology, Bengaluru, Karnataka, India
E-mail:-mohan.bangalore77@gmail.com

Achyutha Prasad N
Professor, Department of Computer Science and Engineering, East West Institute of Technology, Bengaluru, Karnataka, India
Email: achyuth001@gmail.com

Piyush Kumar Pareek
Professor, Department of Computer Science and Engineering & Head of IPR Cell, Nitte Meenakshi Institute of Technology, Bengaluru, Karnataka, India
Email: piyush.kumar@nmit.ac.in

***Abstract*---**Deep Learning has indeed been widely used in many fields/areas of medicinal images classification, and a large number of publications have been published documenting its success. The key for achieving effective diagnosis and therapy is accurate characterization of medical pictures. However, because image interpretation is highly dependent on the subjective opinion of doctors, the results of image processing vary greatly amongst

Manuscript submitted: 18 Feb 2022, Manuscript revised: 09 March 2022, Accepted for publication: 27 April 2022

clinicians at different levels. Picture classification, target identification, and image analysis have all improved dramatically in recent years with environmental image data sets in domain of Image Processing. In this paper, we have presented a systematic survey on feature extracting and classifying the medical images using deep learning methods. Two new ideas are presented in this work. First and foremost, we classified presently trendy publications in a multi-level configuration. Second, this research article concentrates on supervised and poorly supervised learning techniques.

***Keywords*---**medicinal image classification, deep learning, supervised learning, poorly supervised learning.

Introduction

The goal of medicinal image classification is to implement modifications in anatomical structures more clear in images. Because of the significant improvement in diagnosing efficiency and high accuracy, it frequently plays a vital role in computer assisted treatments and cognitive medicines. Scanning techniques such as X-RAY, CT scan, MRI, PET-MRI and Ultrasound, etc. has emerged as the majority image-assisted methods for radiologists and physicians to identify diseases, assess treatment plan, in health care facilities. Regardless of the fact that a variety of algorithms have been described, and also some of them are effective in certain conditions, image classification remains one of the most difficult subjects in computer vision due to the challenges in feature extraction. Medical images are more challenging to identify discriminate characteristics from typical RGB images because, the previous technologies implemented generally suffers from blur, noise, poor contrast, and other issues. Convolutional neural networks (CNN) fruitfully accomplish characteristic depiction of images, and therefore is the top trending subject matter for research in image processing, because of the deep learning techniques. The well built classification systems assigns a relevant tier to every image pixel at the pixel level categorization. In contrast to semantic segmentation, feature extraction requires not just pixel level categorization, but also the distinction of specimens based on specified sections. We concentrate on formation and advancement of deep learning model for medical image classification. Medical imaging is becoming more significant in the early identification, diagnosis, as well as the treatment of diseases. It is also the motive for quicker and more thorough treatment.

Materials and Methods

We examined existing literatures in three areas for supervised learning methods: backbone network selection, network block design, and cost function improvement. The literatures on poorly supervised learning methods are examined on the basis of transfer learning, and interactive classification. This study organizes the literatures significantly differently from previous surveys, making it easier for reader to realize the essential logic along with guiding them in the direction of advancement in medical images classification using deep learning algorithms. (Taghanaki et al., 2020) looked at the evolution of semantic and medical picture segmentations and divided image classification solution in 6 categories. They were deep architectures, data organization, loss function, sequencing model, poorly supervised, and multi-tasking techniques. (Seo et al., 2020) investigated on classic ML methods. They were Markov random fields, k-means clustering, and random forest. Moreover, the authors investigated on the newest deep learning implementations such as ANN, CNN, RNN, and so on, to develop a more comprehensive survey on feature extraction and classification of medical images.

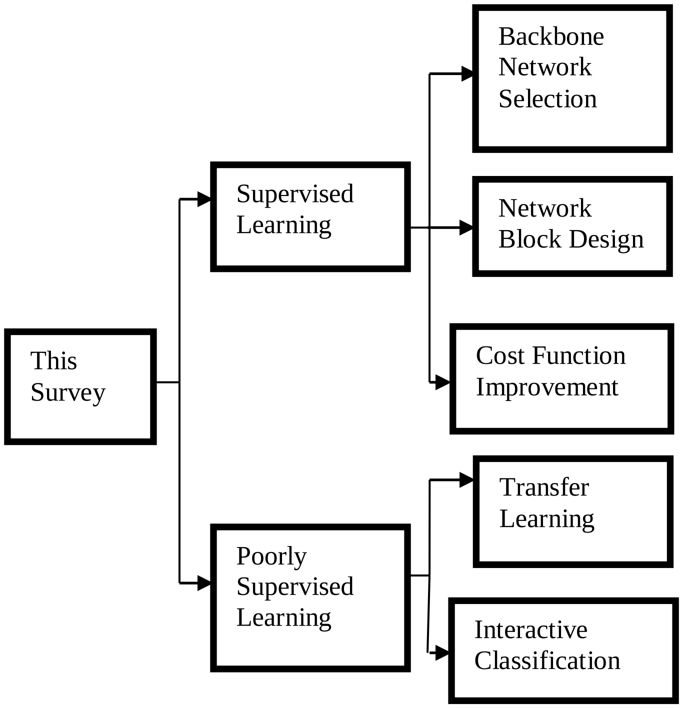

Figure 2(a): An Overview of the Survey

(Tajbakhsh et al., 2020) looked at ways to segment medical images with incomplete datasets, focusing on two primary dataset limitations. They were limited annotations and poor annotations. (Eelbode et al., 2020) examined and summarized the optimization strategies utilised in medical picture classification tasks, which were mainly based, either on Dice scores or Jaccard indices. All of these studies contribute to the advancement of medical picture classification methods.

Supervised learning

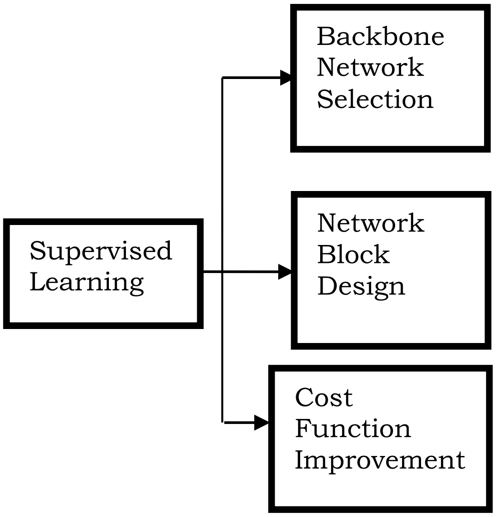

Figure 2(b): Architecture of a Network based on Supervised Learning

Backbone Network Selection:
(Benali et al., 2020) defined backbone as: The feature detection network employed within the Deep CNN architecture is referred to as the “backbone”. The network's input is encoded into a feature representation using this feature extractor. The feature detection system is referred to as the backbone in Deep cnn models and articles. These feature detection systems synthesise information from the image, which are subsequently up-sampled to form structured masks. In order to extract features, CNNs are utilised. AlexNet, VGGNet, and ResNet are just a few of the CNNs accessible. These systems have been assessed on some well used metrics and datasets, including ImageNet, and are mostly used for object computer vision tasks. The classifier in image classification or image processing classifies an unique part of an image, calculates component per image, and calculates the likelihood of matching a class. Object detection, on the other hand, requires the prototype to be able to distinguish several things in a single image as well as provide dimensions that identify the items' places. This demonstrates that object detection are more challenging than image classification. (Ibtehaz et al., 2020) presented MultiResUNet, which includes the Residual Path called ResPath, which requires encoder characteristics to complete additional convolution operations before merging with equivalent decoder features. The “MultiRes U-Net” model outperforms the “standard U-Net”, according to the authors. (BiswajeetPradhan et al., 2021) They also highlighted that the MultiRes U-Net must be responsive to future testing across several modalities. One of the obstacles in biomedical image classification is the variance in the feature points, such as the dimensions of a brain tumour. They integrated the resultant image characteristics after applying additional convolutional filters of size 3x3, 5x5 and 7x7 simultaneously. They also included a residual link, which has been shown to be effective in biomedical image classification. Finally, to accommodate additional spatial information, they added an 1x1 convolutional layer. A MultiRes block is the name for this type of alteration. The fact that the first link connects the encoder as well as decoder

before first pool and in the last deconvolution process is a disadvantage of the skip connections. Because the characteristics from the decoder contained low-level report and the characteristics from the encoder contain high-level report, a likely syntactic gap between the two feature sets was detected. For liver and liver-cancer analysis, (Dey et al., 2020) established a cascading method of two-dimensional as well as three-dimensional networks. The hybrid 2D/3D cascade network may significantly enhance classification precision while also decreasing learning time and cost. To accomplish brain dis-section classification, (Valanarasu et al., 2020) proposed KiUNet, which is cascade network. When detecting tiny anatomical features with fuzzy noise borders, the performance of vanilla U-Net is severely hampered. To solve this problem, the authors developed the Ki-Net, a new over-complete structure in which the intermediate layer's spatial dimension be bigger than the entered figures. As a result, the suggested Ki-Net surpass U-Net in terms of capturing the edges, to improve total classification accurateness. Ki-Net not just increases classification accurateness. Moreover, it gains quick confluence meant for minute anatomical feature and unclear borders because it can leverage both poor tiny edges feature maps as well as bulkier shape feature maps by making use of Ki-Net plus U-Net. A conditional Generative Adversarial Network (cGAN) was presented by (Singh et al., 2020) to segregate breast cancers contained by the target region in mammograms. This network grasps information to detect cancer regions and generate classification outcomes. The network learns to differentiate actual nature of the problem and the generative network's classification results, prompting the generative network to produce trademark that are as accurate as possible. When the quantity of training sample is small, the cGAN works well. (Conze et al., 2020) used torrent prê-trained encoders-decoders as cGAN generator for intestinal multiorgan classification, and the adverse network was used as segregator to enforce the prototype and construct pragmatic organ classifications. (Boutillon et al., 2020) Combined earlier figures with provisional neural network to support prototypes to track overall anatomic features with regard to shape and location details, to formulate classification result as precise as feasible.

Network Block Design

A block design is the rate of occurrence of the construction made up of a set and a family of subgroups called blocks. They are chosen so that the frequency of the components meets specific criteria, resulting in uniformity in the collection of blocks. (Amrouch et al., 2020) The phrase "block design" generally relates to a Balanced Incomplete Block Design (BIBD). It is especially a 2-design, that has historically been the most researched subject due to its use in experimental designs. (Meng et al., 2020) suggested a “V-Net” (LV-Net) which performs a smaller amount of process than V-Net for liver analysis by extending intensity separable complexity to the creation of 3D networks. The attentive parameters generated at different network layers trained on the Clinical Liver dataset were studied using a low-resolution VNet. In the top two network levels, the attentive gateways offer a rough outline of the organs, but not in the lower resolution scenarios. The second classification images formed at lower layers of the protocol stack trained on the Clinical Liver dataset were also studied using the low-resolution VNet. Despite the fact that the major goal of the second classification images is not to refine the final classification formed at the model's last layer, authors were able to see a relationship between the appearance of each term and its activation in the classification points of interest. On the second classification level, the attentive image accurately matches with the organ, however on the first classification level, the attention appears to concentrate on the liver boundaries. Whereas in depth-wise separable, CNN is an excellent strategy to lessen the quantity of prototype performance because it may cause loss of accurateness in medical picture classification, necessitating the use of alternative methods. (Wang et al., 2020) had developed a Non-local U-Net for medical picture classification to solve the difficulties of local convolution. During both up-sampling and down-sampling, the non-native U-Net uses the intra-attention technique as well as universal computing section to take out entire picture's information, which can increase the final classification accuracy. The non-native section may be implemented to advance the performance of various CNN. The attention process can be seen to be effective in boosting image classification accuracy. In reality, while spatial attention seeks out fascinating regions of the image, channel attention seeks out intriguing qualities. When dealing with three dimensional biological images, dimensional data training is more difficult than when working with two dimensional biological images. Because of the unavailability of huge training examples, a wide range of factors and a larger memory is needed. Training is substantially more complex and expensive in order to provide satisfactory predictions. Superposition of multi-scale convolutions was used by (Lei et al., 2021) to liver tumor classification, which shows a significant improvement in accuracy.

Cost Function Improvement

The "objective function" is the function we wish to minimize or maximize. It's also known as the "cost function", "loss function", or "error function" when it is minimized. (Shruti Jadon et al., 2020) The cost function boils down all of the positive and negative characteristics of a potentially complicated system to a single value, a scalar value, that can be used to rank and compare viable solutions. A loss function must always be chosen for calculating the model's error throughout the optimizing phase. As a result, it's critical that the function accurately reflects the design objectives. (Chen et al., 2020) introduced an innovative regularization name depending on Hausdorff distance to strengthen the cross - entropy loss function. The Hausdorff Distance is a phenomenon that classification processes use to track the quality of the system. The ambition of every classification model is to enlarge the Hausdorff Distance. However, it is not generally utilized as a loss function because to its non-convex character. The authors developed three kinds of Hausdorff Distance cost functions, where every individual cost error contains some usage scenarios and guarantees tractability. These three options are based on how Hausdorff Distance can be used as a part of a cost function:

- Calculating the maximum of all Hausdorff errors
- Calculating the lowest error value from the obtained error values via putting a spherical structure of some radius
- Calculating the maximum of a convolution kernel positioned at the peak of lacking classified pixels

(Yao et al., 2020) introduced a “Structural Similarity Loss” (SSL) to accomplish a high optimistic linear association among the ground truth features and the predicted fearures. Structure comparing, Cross-Entropy load coefficient computation, and mini-batch cost determination were the three steps into which the authors divided. The "e-coefficient", that can assess the quality of continuous association between ground truth as well as estimation, was obtained as a part of the Structure comparison as mentioned in this paper:

$$e = \left| \frac{a - \mu_a + C}{\sigma_a + C} - \frac{b - \mu_b + C}{\sigma_b + C} \right|$$

C is a strengthening factor with an experimental value of 0.01. ‘μ_a’ is the localized mean and ‘σ_a’ is the ground truth’s (‘a’) standard deviation. ‘a’ is the central point of the localized area. ‘b’ is the expected probability of the localized area. They employed the degree of correlation as a coefficient for the cross entropy cost function, which is described below.

$$f_{x,y} = (1 * e_{x,y}) > \beta e_{max}$$

(Karimi et al., 2020) reported a process for maternal period brain MRI classification that used a fully CNN architecture with deep monitoring and remaining connectivity and achieved good classification precision. In reality, deep supervision not only enhances network training efficiency while constraining the unfairness and consistency of features extracted in every phases. The diversified and overlapped surface of the organ in both 2D and 3D biological pictures presents a significant challenge to researchers in the classification field. The classification field is poor due to the varying sizes of the organs of the body as well as the unclear boundaries between the tumor site and its surrounding tissues in image processing.

Poorly Supervised Learning

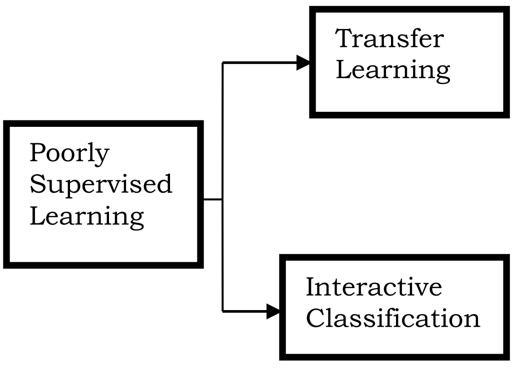

Figure 2(c): Architecture of a Network based on Poorly Supervised Learning

Transfer Learning

"Transfer learning" is a method which is used in Machine Learning method. In this technique, a model formed for one work is utilized as the starting point for a model of dissimilar job. (Subhashis Banerjee et al., 2020) In deep learning, transfer learning effectively works if the model characteristics gained during the first task are generalized. Transfer learning is commonly used: (i) To avoid having to train several machine learning systems from the beginning to fulfill comparable tasks, saving time and resources. (ii) As a cost-cutting measure in areas of machine learning where large amounts of data are required, such as image classification or natural language processing. To carry out syntactic classifications of mechanized instruments using video of vascular generating tumors and surgical techniques, (Kalinin et al., 2020) used multiple models, which were trained in advance on ImageNet as encoders of curved network (U-Shaped). These models were VGG-11, VGG-16, and ResNet-34 networks. (Brochard et al., 2020) utilized VGG-11, which are trained well in advance on ImageNet, as an encoder of a classification system to segment MRI images of the shoulders. Studies showed that using a pre-trained network to improve classification accuracy is beneficial. We can say that a pre-trained system on ImageNet could find out certain general characteristics required for both medicinal as well as natural images, removing the need for re -training while fine-tuning is beneficial to model training. While adapting pre-trained model of natural scenes to medical image processing applications, the domain addictiveness may be a concern. Furthermore, because the pre-trained model frequently depend upon datasets of two-dimensional images, the transfer learning approaches are rarely relevant to three-dimensional medical image processing. If the quantity of medical images datasets containing annotations is high, the impact of pre-training on model's performance may be less. (Deepa et al., 2021) used transfer learning methodology to detect brain tumor. The described network structure is designed using the transfer learning. For 20 iterations, they utilized a batch normalization size of 200. Firstly, the network is trained and certified. Secondly, the system is verified and evaluated with MRI images data. The models sort the raw data into two categories: tumor and non-tumor. As a result, one can detect the existence of a tumor in certain images. The Deep Network Designer is a toolbox in MATLAB which is used for implementation. They presented a comparison of various ResNet variations such as ResNet-50, ResNet-101, and ResNet-152. The process of transfer learning modifies all of the networks. The AlexNet was finely tuned by (Maqsood et al., 2019) for identifying the Alzheimer's disease. The four steps of their methodology are as follows. The intended domain's MRI images are first pre-processed by executing contrasting procedures. Secondly, as a preliminary step for learning the new task, the AlexNet system is pre-trained on ImageNet. Thirdly, AlexNet's convolutional neural networks are fixed, as well as the last 3 fully connected levels, including one softmax layer, one completely connected layer, and one output layer, are replaced with new layers. Finally, through training on the Alzheimer's dataset, the modified AlexNet is fine-tuned. The suggested technique gives the accurate results for the different types of classification problem, according to the experimental findings. (Kute et al., 2019) describes a "component-based face recognition system that was developed utilizing a transfer learning technique for forensic applications". It describes how knowledge gained from one area, such as whole facial images, is utilized to classify face components. However the face and all of its features are different, they transmit traditional details that is utilized to transfer knowledge from one sector to another. Apart from that, incomplete captured faces such as the front, bottom, and top portion, as well as the right-side, left-side, lower-side, and upper-side diagonal, are used to join partial and whole face images.

Interactive Classification

For automated anatomic tagging of coronary arteries, (Yang et al., 2020) presented an uninterrupted conditional residual design "convolutional network CPR-GCN". The authors demonstrated that the GCN-based strategy outperformed traditional and current depth learning-based approaches in terms of performance and resilience. The structure of the chart has excellent information depiction efficiency as well as good characteristic programming capabilities. Therefore, the results obtained from GCN in medical image classifications are encouraging. (Darbeha et al., 2020) introduced SAU-Net, which is concerned with model interpretability and robustness. Using supplementary-shaped streams, the suggested architecture seeks to highlight the problems of poor edge classification performance in medical images. Shape streams and regular texture streams, can record extensive shape dependent information simultaneously. Moreover, the decoder employs both spatial and channel attention structures to give details about learning ability of model at every U-Net level. Finally, one can characterize the extremely triggered area of each and every decoder's block by extracting learnt shapes. The learnt shape maps are further used to determine the correct forms of the model's interesting divisions. The SAU-Net can learn difficult characteristics of things using a gated shape stream. It is a better interpretable model than earlier work. (Kampffmeyer et al., 2020) investigated on uncertainties and interpretability of colorectal polyp syntactic classification in CNN. Authors proposed the key idea of directed back propagation for network gradient interpretation. The gradient correlating with each pixel in input is retrieved through back propagation, allowing the network's features to be displayed. Pixels with positive gradient values in a picture are been given more attention in the back propagation process due to their high relevance. Pixels with negative gradient values are been ignored. The negative gradients may result with noisy representation of descriptive information if they are used in the presentation of key pixels. The back propagation procedure modifies the neural network's back propagation. Hence, the negative valued gradients are set to 0 on every layer. Only positive valued gradients are allowed to surge back through the system and finally display those pixels, avoiding the creation of noisy representations. To increase model's training efficiency, (Glocker et al., 2020) suggested a different learning strategy for classification of anatomical features from unmatched CT scan images and the MRI images, as well as a new cost function employing information characterization. The normalization layer, which is utilised for multiple modalities, is built in distinct variables, whereas CNN layer is built in shared variables. Samples for every modal are loaded individually in each training step. They are forwarded to shared convolutional layers as well as independent normalization layers, where the logarithms for calculating knowledge distillation losses are acquired. (Beyer et al., 2020) introduced the Vision Transformer (ViT), which is used to analyze images easily. A considerable amount of researchers has recently used the transformer to classify medical images. (Adeli et al., 2021) In terms of extracting the features, CNNs offer a big advantage. At the patch level, the low-level factors create the main points, lines, as well as some basic image structures. When we recognize the fundamental visual characteristics, the most troubling information is about the high-level visual syntactic information. A question arises that how the elements interact for the formation of an object, as well as how spatial placement of objects interacts to build an image. Currently, the transformer is much more successful in dealing with these aspects' relationships.

Other techniques implemented

(Gajendra Raut et al., 2020) proposed “Deep Learning Approach for Brain Tumor Detection and Segmentation” which is a CNN model for brain tumour detection. To begin, brain MRI scans are enhanced in order to gather enough data for deep learning. After that, the image is pre-processed to reduce noise and prepare them for the next stage. The proposed system is trained on pre-processed MRI brain pictures and uses characteristics extracted during training to classify newly input images as tumorous or normal. Back propagation is used to reduce error and produce more accurate outcomes. To construct the image, autoencoders are employed to remove irrelevant features, and the tumour region is then segmented using the K-Means technique. (Aryan Sagar Methil et al., 2021) proposed “Brain Tumor Detection using Deep Learning and Image Processing”. A unique approach for detecting brain cancers from diverse brain images is based on performing several image pre-processing methods such as histogram equalization, followed by a CNN. The experiment was done out on a dataset that included tumours of various shapes, sizes, properties, and positions. For the classification challenge, a CNN was used. CNN acquired a recall of 98.55 percent on training dataset set and 99.73 percent on the evaluation data.

Results and Discussions

The suggested Ki-Net surpass U-Net interms of capturing the edges, to improve total classification accurateness. The attentive parameters generated at different network layers trained on the Clinical Liver dataset were studied using a low-resolution VNet. In reality, deep supervision not only enhances network training efficiency while constraining the unfairness and consistency of features extracted in every phases. The diversified and overlapped surface of the organ in both 2D and 3D biological pictures presents a significant challenge to researchers in the classification field. The classification field is poor due to the varying sizes of the organs of the body as well as the unclear boundaries between the tumor site and its surrounding tissues in image processing. We can say that a pre-trained system on ImageNet could find out certain general characteristics required for both medicinal as well as natural images, removing the need for re -training while fine-tuning is beneficial to model training. Vision Transformer accomplishments in medical image classification jobs should not be overlooked. Some conventional components of CNN, including activation functions, dropouts, and batch normalization, may become roadblocks to growth.

Conclusion

The purpose of this study is to provide an overview of the methodologies often used to classify medical images. These methodologies can also be used to detect various diseases such as brain tumors, malaria detection from blood swarm images, covid-19 via chest X-RAY, heart disorders, kidney diseases, liver tumor, breast cancer detection, and many more. Different strategies for medical image classification are discussed in this paper. This work is done after a review of 42 research papers. The key for achieving effective diagnosis and therapy is accurate characterization of medical pictures. However, because image interpretation is highly dependent on the subjective opinion of doctors, the results of image processing vary greatly amongst clinicians at different levels. This study organizes the literatures significantly differently from previous surveys, making it easier for reader to realize the essential logic along with guiding them in the direction of advancement in medical images classification using deep learning algorithms. All of these studies contribute to the advancement of medical picture classification methods. Various researches have produced extraordinary outcomes by defying convention. Such concepts are equally deserving of further investigation.

Acknowledgments

I extend my deep sense of sincere gratitude to Dr. Channakesavalu K, Principal, East West Institute of Technology, Bengaluru, for having permitted to carry out the survey on "AUTOMATED MEDICAL IMAGE CLASSIFICATION USING DEEP LEARNING" successfully.
I express my heartfelt sincere gratitude to Dr. Achyutha Prasad N, Head, Department of Computer Science and Engineering, East West Institute of Technology, Bengaluru for his valuable guidance, encouragement and suggestions.
I would like to express my sincere thanks to my internal guide Dr. B.R. Mohan, Professor, Department of Computer Science and Engineering, East West Institute of Technology, Bengaluru for his valuable guidance, encouragement and suggestions.
I would like to express my deep sense of sincere gratitude to my external guide Dr. Ashapurna Marndi, Senior Scientist, CSIR Fourth Paradigm Institute, NAL Belur Campus, Bangalore – 560037 for her valuable guidance, encouragement and suggestions.
I would like to thank all the Teaching, Technical faculty and supporting staff members of Department of Computer Science and Engineering, East West Institute of Technology, Bengaluru, for their valuable suggestions and support.
Finally, I would like to thank my Parents for their support.

References

S. A. Taghanaki, K. Abhishek, J. P. Cohen, J. Cohen-Adad, and G. Hamarneh, "Deep semantic segmentation of natural and medical images: A review," Artif. Intell. Rev., pp. 1–42, 2020.

H. Seo, M. Badiei Khuzani, V. Vasudevan, C. Huang, H. Ren, R. Xiao, X. Jia, and L. Xing, "Machine learning techniques for biomedical image segmentation: An overview of technical aspects and introduction to state-of-art applications," Med. Phys., vol. 47, no. 5, pp. e148–e167, 2020.

N. Tajbakhsh, L. Jeyaseelan, Q. Li, J. N. Chiang, Z. Wu, and X. Ding, "Embracing imperfect datasets: A review of deep learning solutions for medical image segmentation," Med. Image Anal., p. 101693, 2020.

T. Eelbode, J. Bertels, M. Berman, D. andermeulen, F. Maes, R. Bisschops, and M. B. Blaschko, “Optimization for medical image segmentation: theory and practice when evaluating with dice score or jaccard index,” IEEE Trans. Med. Imaging, vol. 39, no. 11, pp. 3679– 3690, 2020.

N. Ibtehaz and M. S. Rahman, “Multiresunet: Rethinking the u-net architecture for multimodal biomedical image segmentation,” Neural Network, vol. 121, pp. 74–87, 2020.

R. Dey and Y. Hong, “Hybrid cascaded neural network for liver lesion segmentation,” Proc. IEEE Int. Symp.Biomed. Imag. (ISBI), pp. 1173– 1177, 2020.

J. M. J. Valanarasu, V. A. Sindagi, I. Hacihaliloglu, and V. M. Patel, “Kiu-net: Towards accurate segmentation of biomedical images using over-complete representations,” roc. Int. Conf. Med. Image Comput. Comput. Assist. Intervent.(MICCAI), pp. 363–373, 2020.

V. K. Singh, H. A. Rashwan, S. Romani, F. Akram, N. Pandey, M. M. K. Sarker, A. Saleh, M. Arenas, M. Arquez, D. Puig et al., “Breast tumor segmentation and shape classification in mammograms using generative adversarial and convolutional neural network,” Expert Syst. Appl., vol. 139, p. 112855, 2020.

P.-H. Conze, A. E. Kavur, E. C.-L. Gall, N. S. Gezer, Y. L. Meur, M. A. Selver, and F. Rousseau, “Abdominal multi-organ segmentation with cascaded convolutional and adversarial deep networks,” arXiv preprint arXiv:2001.09521, 2020.

A. Boutillon, B. Borotikar, V. Burdin, and P.-H. Conze, “Combining shape priors with conditional adversarial networks for improved scapula segmentation in mr images,” Proc. IEEE Int. Symp. Biomed. Imag. (ISBI), pp. 1164–1167, 2020.

T. Lei, W. Zhou, Y. Zhang, R. Wang, H. Meng, and A. K. Nandi, “Lightweight v-net for liver segmentation,” IEEE Int. Conf. Acoust. Speech Signal Process. (ICASSP), pp. 1379–1383, 2020.

Z. Wang, N. Zou, D. Shen, and S. Ji, “Non-local u-nets for biomedical image segmentation.” Proc. AAAI Conf. Artif. Intell., pp. 6315–6322,2020.

T. Lei, R. Wang, Y. Zhang, Y. Wan, C. Liu, and A. K. Nandi, “Defednet: Deformable encoder decoder network for liver and liver tumor segmentation,” IEEE Transactions on Radiation and Plasma Medical Sciences, p. 10.1109/TRPMS.2021.3059780, 2021

X. Li, L. Yu, H. Chen, C.-W. Fu, L. Xing, and P.-A. Heng, “Transformation-consistent self ensembling model for semisupervised medical image segmentation,” arXiv preprint arXiv:1903.00348, 2020.

H. Dou, D. Karimi, C. K. Rollins, C. M. Ortinau, L. Vasung, C. Velasco-Annis, A. Ouaalam, X. Yang, D. Ni, and A. Gholipour, “A deep attentive convolutional neural network for automatic cortical plate segmentation in fetal mri,” arXiv preprint arXiv:2004.12847, 2020.

A. A. Kalinin, V. I. Iglovikov, A. Rakhlin, and A. A. Shvets, “Medical image segmentation using deep neural networks with pre-trained encoders.” Springer, 2020, pp. 39–52.

P.-H. Conze, S. Brochard, V. Burdin, F. T. Sheehan, and C. Pons, “Healthy versus pathological learning transferability in shoulder muscle mri segmentation using deep convolutional encoder-decoders,” Comput. Med. Imaging Graph, p. 101733, 2020.

H. Yang, X. Zhen, Y. Chi, L. Zhang, and X.-S. Hua, “Cpr-gcn: Conditional partial-residual graph convolutional network in automated anatomical labeling of coronary arteries," Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 3803– 3811, 2020.

J. Sun, F. Darbeha, M. Zaidi, and B. Wang, "Saunet: Shape attentive u-net for interpretable medical image segmentation," arXiv preprint arXiv:2001.07645, 2020.

K. Wickstrøm, M. Kampffmeyer, and R. Jenssen, "Uncertainty and interpretability in convolutional neural networks for semantic segmentation of colorectal polyps," Med. Image Anal., vol. 60, p. 101619, 2020.

Q. Dou, Q. Liu, P. A. Heng, and B. Glocker, "Unpaired multi-modal segmentation via knowledge distillation," IEEE Trans. Med. Imaging, 2020.

A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly et al., "An image is worth 16x16 words: Transformers for image recognition at scale," arXiv preprint arXiv:2010.11929, 2020.

J. Chen, Y. Lu, Q. Yu, X. Luo, E. Adeli, Y. Wang, L. Lu, A. L. Yuille, and Y. Zhou, "Transunet: Transformers make strong encoders for medical image segmentation," arXiv preprint arXiv:2102.04306, 2021.

Y. Gao, M. Zhou, and D. Metaxas, "Utnet: A hybrid transformer architecture for medical image segmentation," arXiv preprint arXiv:2107.00781, 2021.

J. M. J. Valanarasu, P. Oza, I. Hacihaliloglu, and V. M. Patel, "Medical transformer: Gated axial-attention for medical image segmentation," arXiv preprint arXiv:2102.10662, 2021.

H. Cao, Y. Wang, J. Chen, D. Jiang, X. Zhang, Q. Tian, and M. Wang, "Swin-unet: Unet-like pure transformer for medical images segmentation," arXiv preprint arXiv:2105.05537, 2021

Deepa P L, Narain Ponraj and Sreena V G "A Comparative Analysis of Deep Neural Networks for Brain Tumor Detection", 2021 3rd International Conference on Signal Processing and Communication (ICPSC)

Divyamary.D, Gopika.S, Pradeeba.S and Bhuvaneswari.M "Brain Tumor Detection from MRI Images using Naive Classifier", 2020 6th International Conference on Advanced Computing & Communication Systems (ICACCS)

Gajendra Raut, Aditya Raut, Jeevan Bhagade, Jyoti Bhagade and Sachin Gavhane "Deep Learning Approach for Brain Tumor Detection and Segmentation", 2020 IEEE International Conference on Convergence to Digital World – Quo Vadis (ICCDW 2020)

Aryan Sagar Methil, "Brain Tumor Detection using Deep Learning and Image Processing", IEEE 2021

Shuai Zhao, Boxi Wu, Wenqing Chu, Yao Hu, and Deng Cai. "Correlation maximized structural similarity loss for semantic segmentation." arXiv preprint arXiv:1910.08711, 2019.

M. Maqsood, F. Nazir, U. Khan, F. Aadil, H. Jamal, I. Mehmood, and O. Song, "Transfer learning assisted classification and detection of Alzheimer's disease stages using 3D MRI scans," Sensors, vol. 19, no. 11, pp. 1–19, Jun. 2019.

Kute, R.S., Vyas, V. and Anuse, "A Component-based face recognition under transfer learning for forensic applications." Information Sciences, 476, (2019) 176-191

Wang, F.; Cheng, J.; Liu, W.; Liu, H." Additive margin softmax for face verification". IEEE Signal Process. Lett. 2018, 25, 926–930.

Zhu, Q.; Zhang, P.;Wang, Z.; Ye, X. “A new loss function for CNN classifier based on predefined evenly distributed class centroids.” IEEE Access 2019, 8, 10888–10895.

Luo, W.; Li, Y.; Urtasun, R.; Zemel, R. “Understanding the Effective Receptive Field in Deep Convolutional Neural Networks.” arXiv 2017, arXiv:1701.04128. VGG

Kolesnikov, A.; Beyer, L.; Zhai, X.; Puigcerver, J.; Yung, J.; Gelly, S.; Houlsby, N.”Large Scale Learning of General Visual Representations for Transfer”. arXiv 2019, arXiv:1912.11370.

BiswajeetPradhan, Abolfazl Abdollahi “Integrating semantic edges and segmentation information for building extraction from aerial images using UNet” Machine Learning with Applications 6 (2021) 100194.

Nabil Ibtehaz and M. Sohel Rahman, “MultiResUNet : Rethinking the U-Net Architecture for Multimodal Biomedical Image Segmentation” arXiv:1902.04049v1 [cs.CV] 11 Feb 2019

Subhashis Banerjee, Student Member, IEEE Supervisor: Francesco Masulli, Senior Member, IEEE and Sushmita Mitra, Fellow, IEEE Brain Tumor Detection and Classification from Multi-Channel MRIs using Deep Learning and Transfer Learning.

Shruti Jadon, IEEE Member “A survey of loss functions for semantic segmentation.” arXiv:2006.14822v4 [eess.IV] 3 Sep 2020.

Benali Amjoud, A., Amrouch, M. (2020). “Convolutional Neural Networks Backbones for Object Detection. Image and Signal Processing.” ICISP 2020.

Piyush Kumar Pareek et al, ‘Survey on Challenges in Devops ’, International Journal of Innovative Research in Computer Science & Technology (IJIRCST), ISSN: 2347-5552, Volume-4, Issue-5, September-2016.

Dr.Piyush Kumar Pareek et al, ‘Education Data Mining –Perspectives of Engineering Students ’, International Journal of Innovative Research in Computer Science & Technology (IJIRCST), ISSN: 2347-5552, Volume-4, Issue-5, September-2016.

Dr.Piyush Kumar Pareek et al, ‘A survey on approaches for predicting performance of students’,International Journal of Engineering Research and Science, ISSN No.2395-6992 Paper Id:IJOER-Jun-2016-25.

Dr.Piyush Kumar Pareek et al, ‘A survey on Long term product planning and requirements prioritization to customer value creation’, International Journal of Engineering Research and Science, ISSN No.2395-6992 Paper Id: IJOER-Jun-2016-27.

Dr.Balakrishna R, Piyush Kumar Pareek et al, ’Study on Six Sigma approach to improve the quality of process outputs in business processes in Small & Medium Level Software Firms’ Springer AISC Series/ SCOUPS INDEXED JOURNAL, Paper Id : IT -221-ICPCIT2015 , June 2015.

Dr.Balakrishna R, Piyush Kumar Pareek et al, ’Data Mining for Healthy Tomorrow with the implementation of Software Project Management technique’, Springer AISC Series/ SCOUPS INDEXED JOURNAL, Paper Id : IT -187-ICPCIT2015, June 2015.

Piyush Kumar Pareek & Dr. A. N. Nandakumar, ’To Implement Lean software development frame- work for minimizing waste in terms of non-value added activities’, Research Publishing, Jain University ICISTSI-15 , Innovative Partners for Publishing Solutions, Singapore (May 2015).

Piyush Kumar Pareek & Dr.A.N.Nandakumar, 'Identifying Wastes in software, International Journal of Engineering Studies and Technical Approach'. January Issue 2015.

Piyush Kumar Pareek & Dr.A.N.Nandakumar, 'Failure Mode Effective Analysis of Requirements Phase in small software Firms', Paper ID: ICSTM/YMCA/2015/292, International Conference on Science, Technology and Management (ICSTM-2015). International Journal of Advance Research in Science and Engineering (IJARSE, ISSN- 2319-8354, Impact Factor- 1.142) [www.ijarse.com], Special Issue Jan2015.

Mr. Piyush Kumar Pareek, Dr. A. N. Nandakumar, 'Lean software development Survey on Agile and Lean usage in small and medium level firms in Bangalore' , International Journal of Advanced Research in Computer Science and Software Engineering , Volume 4, Issue 12, December 2014 , ISSN: 2277 128X .pp 1-7 Impact Factor : 2.08.

Mr.Piyush Kumar Pareek, Dr. A. N. Nandakumar, 'Lean software development Survey on Benefits and challenges in Agile and Lean usage in small and medium level firms in Bangalore' , International Journal of Advanced Research in Computer Science and Software Engineering , Volume 4, Issue 12, December 2014 , ISSN: 2277 128X .pp 1-11 Impact Factor : 2.08.

Piyush Kumar Pareek , Dr.Praveen Gowda , et al 'Ergonomics in a Foundry in Bangalore to improve productivity',International Journal of Engineering and Social Science , ISSN: 2249- 9482 ,Volume 2,Issue 5 (May 2012) , pp 1-6.

Piyush Kumar Pareek, Dr. Vasanth Kumar S A , et al 'Reduction of Cycle Time By Implementation of a Lean Model Carried Out In a Manufacturing Industry', International Journal of Engineering and Social Science , ISSN: 2249-9482,Volume 2,Issue 5 (May 2012) , pp 114-123.

Piyush Kumar Pareek , Dr.Praveen Gowda, et al 'FMEA Implementation in a Foundry in Ban- galore to Improve Quality and Reliability',International Journal of Mechanical Engineering and Robotics Research, ISSN :2278-0149,Volume 1,Issue 2(June 2012),pp 81-87.

Piyush Kumar Pareek, Dr.Vasanth Kumar S A , et al 'Implementation of a Lean Model for Carrying out Value Stream Mapping in a Manufacturing Industry', International Journal of Mechanical Engineering and Robotics Research, ISSN :2278-0149,Volume 1,Issue 2(June 2012),pp 88-95.

Piyush Kumar Pareek, Dr. A. N. Nandakumar, et al 'Methodology and Functioning of Project Management Techniques in Agile Software Development Process', International Journal of Research in IT, Management and Engineering, ISSN: 2249-1619, Volume2, Issue12 (December2012), pp 76-85.

N. A. Prasad and C. D. Guruprakash, "An ephemeral investigation on energy proficiency mechanisms in WSN," 2017 3rd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Tumkur, 2017, pp. 180-185.

A. P. N and C. D. Guruprakash, "A Relay Node Scheme for Energy Redeemable and Network Lifespan Enhancement," 2018 4th International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Mangalore, India, 2018, pp. 266-274.

Achyutha Prasad, N., Guruprakash, C.D., 2019. A relay node scheme of energy redeemable and network lifespan enhancement for wireless sensor networks and its analysis with standard channel models. International Journal of Innovative Technology and Exploring Engineering 8, 605–612.

Achyutha Prasad, N., Guruprakash, C.D., 2019. A relay mote wheeze for energy saving and network longevity enhancement in WSN. International Journal of Recent Technology and Engineering 8, 8220–8227. doi:10.35940/ijrte.C6707.098319.

Achyutha Prasad, N., Guruprakash, C.D., 2019. A two hop relay battery aware mote scheme for energy redeemable and network lifespan improvement in WSN. International Journal of Engineering and Advanced Technology 9, 4785–4791. doi:10.35940/ijeat.A2204.109119.

Rekha VS, Siddaraju., “An Ephemeral Analysis on Network Lifetime Improvement Techniques for Wireless Sensor Networks”, International Journal of Innovative Technology and Exploring Engineering, vol. 8, issue 9, 2278-3075, pp. 810–814, 2019.

Prasad N. Achyutha, Sushovan Chaudhury, Subhas Chandra Bose, Rajnish Kler, Jyoti Surve, Karthikeyan Kaliyaperumal, "User Classification and Stock Market-Based Recommendation Engine Based on Machine Learning and Twitter Analysis", Mathematical Problems in Engineering, vol. 2022, Article ID 4644855, 9 pages, 2022. https://doi.org/10.1155/2022/4644855.

Achyutha, P. N., Hebbale, S., & Vani, V. (2022). Real time COVID-19 facemask detection using deep learning. International Journal of Health Sciences, 6(S4), 1446–1462. https://doi.org/10.53730/ijhs.v6nS4.6231.

Manjunatha Kumar, B., M.Siddappa, D., & J.Prakash, D. (2018). Kannada word sense disambiguation by finding the overlaps between the concepts. International Journal of Engineering & Technology, 7(2.6), 189-192. https://dx.doi.org/10.14419/ijet.v7i2.6.10565.

Kumar, BH Manjunatha, and M. Siddappa. "Kannada word sense disambiguation using semantic relations." Journal of Physics: Conference Series. Vol. 1767. No. 1. IOP Publishing, 2021.

Kalshetty, J. N., Achyutha Prasad, N., Mirani, D., Kumar, H., & Dhingra, H. (2022). Heart health prediction using web application. International Journal of Health Sciences, 6(S2), 5571–5578. https://doi.org/10.53730/ijhs.v6nS2.6479.

R. V S and Siddaraju, "Defective Motes Uncovering and Retrieval for Optimized Network," 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), 2022, pp. 303-313, doi: 10.1109/ICCMC53470.2022.9754109.

N. G and G. C. D, "Unsupervised Machine Learning Based Group Head Selection and Data Collection Technique," 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), 2022, pp. 1183-1190, doi: 10.1109/ICCMC53470.2022.9753995.

Jipeng, T., Neelagar, M. B., & Rekha, V. S. (2021). Design of an embedded control scheme for control of remote appliances. Journal of Advanced Research in Instrumentation and Control Engineering, 7(3 & 4), 5-8.