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An Evaluation of the Transformative Role of Deep Learning in Medical Image Classification for Healthcare Improvement

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Abstract. The quickly developing field of clinical picture order has drawn in specialists from a wide assortment of fields, including PC sciences, applied math, designing, measurements, physical science, science, and medication. Clinical practice as of now utilizes PC helped analytic handling. The work of many imaging modalities and the quick improvement of innovation made further difficulties. Handling and assessing a huge amount of pictures to give great information to sickness conclusion and therapy is one of these troubles. The objective of this course is to start understudies' advantage in additional examination and concentrate in the subject while acquainting them with the essential ideas and methods of clinical picture grouping. Various clinical therapies and the fast progression of clinical information have helped humanity and society overall. Ongoing advances in imaging innovation have made it workable for PC vision analysts to address the open exploration issue of independently perceiving clinical pictures. A few AI and profound learning forecast models are utilized to order symptomatic pictures from datasets. Prescient model investigation might be surveyed utilizing execution markers like F1-Score, exactness, review, and accuracy. Notwithstanding, looking at the activity of a few learning models is in many cases more useful. Research demonstrates that the exactness of order has worked on by 96%. In light of the assessment, we can utilize the profound learning thought and the component change method to expand the arrangement exactness of clinical pictures and empower exact finding. The improvement of PC and picture innovation altogether affects the clinical imaging area. Clinical picture grouping has filled in prevalence as symptomatic exactness is affected by the nature of clinical imaging. A basic technique for putting away such point-by-point pictures is expected for clinical applications that need to save and recover pictures for some time in the future.

Keywords: Medical Image Categorization, Computer-Aided Diagnostic, Machine Learning, Deep Learning, F1-Score, Accuracy.

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I. INTRODUCTION

In recent years, deep neural networks and image processing have been used, among other things, to help with problem solving and sickness diagnosis. Both conventional and cutting-edge deep learning methods may be used to classify images of medical conditions. The use of contemporary methods in this study is justified since they provide the basis for developing an end-to-end model capable of identifying the categorization labels of unprocessed medical pictures [1]. However, they shouldn't be utilized for medical picture categorization because of the model layers' significant limitations and expensive computing costs. Conventional techniques for medical image classification, however, rely on the unique training data that each picture in the collection offers. DNA microarray analysis is a crucial technique for categorization genes associated with cancer. The large dimensions of the data make classification challenging. Therefore, to get highly predictive gene characteristics without compromising accuracy, the dimension must be decreased. Prior research has focused on either reducing gene characteristics or increasing classification accuracy [2]. One of the most significant uses of molecular biology for cancer diagnosis nowadays is the analysis of microarray data. Finding a set of genes with the least inner similarity and the greatest relevance to the target class is known as gene selection, and it is one of the primary objectives of microarray data processing. To lower the dimensionality of the data, repetitive, noisy, or superfluous information may be eliminated [3].

Previously, clinical picture investigation was finished utilizing low-level techniques including thresholding, region development, and edge following [4]. In the in the mean-time, as the sum and variety of clinical imaging information have expanded, AI strategies for clinical picture translation have additionally evolved. Be that as it may, since these techniques depend on physically made highlights, calculation advancement includes human work. These weaknesses in ordinary AI techniques led to the idea of counterfeit brain organizations (ANNs). Factors like PC handling power and information availability help in the formation of ANNs [5]. The coming of profound learning strategies like convolutional brain networks has extended the chance of mechanizing clinical picture handling. Convolutional brain organizations (CNNs) are one sort of brain network planned to deal with visual info. CNN utilizes direct numerical ideas to track down designs in a picture, expanding the versatility of picture characterization. Dissimilar to early CNN models that just comprised of convolutional layers stacked on top of one another, cutting edge CNN plans like as Beginning, ResNet, and DenseNet give new and imaginative techniques to develop convolutional layers such that upgrades learning proficiency [6].

CNN may likewise be utilized to remove highlights. The objective of component extraction is to change over crude pixel information into reasonable mathematical attributes while keeping up with the data in the first informational index. CNNs may extract complex properties that reflect the picture in a much more comprehensive way than traditional feature extractors. Following that, the characteristics are either used for categorization using standard machine learning techniques or supplied into a classifier network [7].

There are issues with CNN's utilization in radiography, notwithstanding the way that profound CNN plans give best in class capacities for PC vision assignments. Goodfellow et al. (2014) found that adding a little measure of commotion to the first information could promptly fool brain networks into distinguishing objects inaccurately [8]. Additionally, CNN needs a huge number of radiological pictures with accurate annotations since the amount of input data often impacts how effectively deep learning works. However, creating these kinds of databases is expensive and time-consuming in the medical field.

The disadvantage of using conventional techniques is that they may result in a system that is unable to effectively build models or representations. Several methods have been developed to speed up the time-consuming process of processing medical images. Medical image dispensation, image segmentation, image interpretation and interpolation, CAD-based diagnosis, picture fusion and classification, and other areas have significantly improved with the use of various AI and ML techniques [2–6].

The main contributions of this study are summarized as follows:

(i) We have proposed a deep learning model that combines high-level traits and conventional characteristics to recognize medical images. It trained the RNN model directly using the feature transform described in [7]. Conventional medical image components might be used to improve the deep model's interpretability and achieve optimum performance.

(ii) Two techniques for integrating high-level and conventional features have been implemented. One approach is to assign a fixed argument representation of the proposition between the conventional features and high-level qualities. This is due to the fact that the conventional method is time-consuming, difficult to utilize, and arduous.

The following is how the paper is written after the introduction: An overview of several photo categorization techniques is given in section II. Section III explains how to identify the issue. In Section IV, describe the deep learning techniques.

Comparative analysis is covered in section V. Section VI presents a concise synopsis of the proposed method and related framework. The expected outcome based on the recommended technique is shown in Section VII.

II. BACKGROUND

According to Saberi et al. [1], gene expression data has become more significant for machine learning and computational biology applications in recent years. Dimensionality reduction methods based on matrix factorization have been frequently employed in gene expression research. The effectiveness and dependability of these systems may be enhanced in the future. The work by Seetharaman et al. [2] shows how DNA microarray analysis is often used to categorize genes linked to cancer. Because of the size of the data collection, classification is challenging. Therefore, it is crucial to minimize the dimension and acquire highly predictive gene characteristics without compromising accuracy. Researchers have previously attempted to increase classification accuracy or decrease gene characteristics. The creators give a connection highlight determination channel and the twofold bat calculation (BBA) with covetous hybrid to tackle the multi-objective issue of giving diminished quality elements OK order precision.

One of the primary applications of atomic science for disease localization is microarray information management, as noted by Azadifar et al. [3]. One of the main challenges in microarray data processing is identifying a set of attributes with the highest external similarity, which is often associated with the target class. Eliminating unnecessary, noisy, or duplicated information reduces the dimension of the data. Considering the concept of the chart, this study provides a new method for finding tumors with improved selection. Both the guided and unguided modes employ influential informal community indicators to evaluate traits, such as highest weighted club rules and edge centrality. Microarray data is essential for illness categorization and prognosis, according to Zhang et al. [4], which is why computer science and bioinformatics have prioritized this area of study. A number of AI systems have been used to classify and predict illness using microarray data. However, in earlier methods, the degree of articulation of a selected set of attributes was heavily weighted as an illustrative quality. These methods rely on insufficient design-relationship information. But as of right now, there is no way to assess if an element is being used overtly in quality determination procedures.

E. Pashaei et al. [5] claim that two popular contemporary metaheuristics, the parallel dark opening calculation (BBHA) and the paired dragonfly calculation (BDF), provided a unique half-and-half approach for resolving the quality choice conundrum. Existing algorithms have struggled to distinguish disease-related data from a multitude of irrelevant characteristics; therefore hybridization attempts to find a small and consistent set of discriminative properties without sacrificing order exactness. Cream calculations are useful tools for managing improvement requests, but they haven't been used extensively in the quality assurance system so far, according to Tavasoli et al. [6]. A considerably modified microarray data gathering method with a more stringent quality subset assurance mechanism is presented in this study. The suggested technique reduces the dimensionality of the data and the time investment by using a five-norm outfit-remember option for light of covering methods.

Khurma et al. [7] guarantee that quality choice (GS) is a captivating subject in medication. This is on the grounds that microarray datasets frequently incorporate countless qualities along with few patient examples. Finding the most significant qualities is perhaps of the most vital first stage in making precise disease characterization calculations. Two new wellness works that are pertinent to GS are introduced in this paper and might be utilized with Parallel Harris Falcons Enhancement (BHHO). The essential goal is to pick a restricted arrangement of qualities that yields a superior level of characterization exactness. The quantity of qualities and classification exactness are adjusted by the primary wellness capability. As per Abdul et al. [8], the mix of information mining and AI (ML) has delivered a few helpful applications for quality choice examination. In this review, we look at the exploration on quality determination techniques drove by AI. Consider utilizing a high-layered quality methodology while taking care of information into a classifier. One meaning of directed learning will be learning under the cautious oversight of a well-informed authority.

Reproducers have been really buckling down throughout the course of recent years to further develop the development rate and feed productivity of ovens, as indicated by a concentrate by Hartcher and partners [9]. As an outcome, meat-creating birds are more powerless against issues including feeble legs, coronary illness, and early mortality, while reproducing birds are compelled to get through serious dietary limitations. Zahoor et al. [10] Various component determination and characterization strategies, both boundary based and boundary free, have been introduced in the writing. The previous is faster yet may bring about neighborhood maxima, while the last option utilizes dataset-explicit boundary acclimation to increment precision. In any case, a model's exactness doesn't liken to its believability. Thusly, further examinations on summed up enhancement are as yet required.

III. PROBLEM IDENTIFICATION AND OBJECTIVES

Problem Identification in Classifying Medical Images [11-12].

- Data-related problems: inconsistent data, bias, expert reliance, variability, and insufficient dataset size and quality.
- Problems with annotation and labelling include interpretability, model complexity, and expert dependency and inconsistency.
- Operational and integration challenges: Real-time processing requirements and smooth integration into current systems.
- Ethical and regulatory concerns: Addressing possible biases in AI models and adhering to data protection and medical device regulations.
- Requirements for resources: substantial hardware and substantial financial considerations.
- Multidisciplinary approach: cooperation between ethicists, medical experts, computer scientists, and regulatory bodies.

Objectives for Medical Image Classification [13].

- Increase Diagnostic Accuracy: Create and verify deep learning models to increase the precision of illness diagnosis.
- Enhance Early Detection: To spot early illness trends in medical photos, apply sophisticated image classification algorithms.
- Boost Processing Efficiency: Use models that analyze and interpret medical pictures more quickly than conventional techniques.
- Promote Greater Accessibility: Develop effective and scalable approaches for various healthcare environments.
- Improve Model Interpretability: Create strategies to make deep learning models easier to understand.
- Assure Generalization and Robustness: Create and train models that are both generalizable to many contexts and populations.

IV. DEEP LEARNING

Deep learning methods model data using intricate frameworks that carry out several non-linear changes at once. The basic components of deep learning are neural networks, which may be combined to create deep neural networks. These methods have enabled significant progress in several domains, including as voice recognition, computer vision, facial recognition, text categorization (including spam detection), and ALP [14]. Figure 1 shows how the way the human brain processes information serves as an inspiration for Deep Learning, a branch of machine learning. By using a wealth of data to map input to labels, deep learning may operate without the need for human-developed rules. Artificial neural networks (ANNs) are used in the construction of DL, and each ANN layer provides a unique interpretation of the input data [15–16].

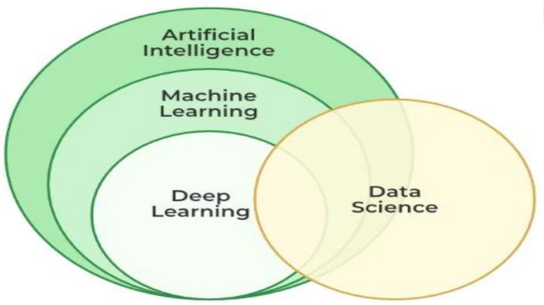

Figure 1: Organization of Deep Learning (Source: https://www.geeksforgeeks.org/introduction-deep-learning/)

Ordinary AI methods need various moves toward achieve the order task, including pre-handling, highlight extraction, cautious component choice, learning, and characterization. The adequacy of AI calculations is likewise essentially affected by highlight determination [16]. One-sided highlight determination might prompt wrong class segregation. Dissimilar to conventional ML methods, DL can consequently learn include sets for different applications. DL might be utilized to all the while learn and group (Fig. 2) [21].

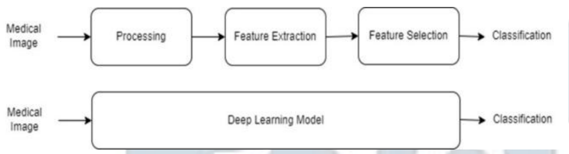

Figure 2: The distinction between conventional machine learning and deep learning (Source: Self Design)

DL's recent rise to prominence as a preferred ML approach is largely due to big data's fast expansion in significance. Its distinctive performance for a wide range of machine learning applications is constantly being improved, and it has accelerated the development of several learning domains, such as object identification, image recognition, and picture super-resolution [13–17].

V. COMPARATIVE ANALYSIS

Biological learning has consistently outperformed the state-of-the-art in machine learning. However, as deep learning (DL) has developed, researchers and scientists have developed techniques for efficiently training different DL neural networks to provide outputs that are comparable to those of real neurons [18]. Expected results are difficult to get since biological neurons are more intricate and have more complex functions than contemporary artificial neurons. While the initial set of neurons to process information is tuned to a certain set of blobs and edges, other parts of the brain could be more responsive to other complex structures, such as faces [19]. This requires a second adjustment of the original features since working directly on inputs cannot create complex structures with enough information to differentiate across classes.

Before DL, models for the concept were created using hierarchical feature learning; however, these models had significant drawbacks, such fading gradient. Architectures perform poorly because these gradients are too small to provide a learning signal for just deep layers, in contrast to straightforward learning algorithms like Support Vector Machines [20]. For training topologies with hundreds of layers and non-linear hierarchical data structures, DL used techniques to get around the issue of vanishing gradients. The gradient flow created by combining graphics processing units (GPUs) with activation functions has led to the rise in popularity of deep learning. There were no problems training models with this gradient flow. These methods seem to affect many domains, including voice recognition, computer vision, and natural language processing (NLP), all of which show significant performance improvements over state-of-the-art approaches in their respective domains. Numerous layers make up several potent deep learning frameworks, such as fully connected, convolutional, and recurrent layers. In addition to several regularization approaches, they are often trained using a variant of the stochastic gradient descent methodology. The widespread use of DL models has led to the development of many distinct DL software environments, which have facilitated the effective development and use of enhanced methods [21–23].

To generate predictions about fresh data, the DL model follows a simple three-step process: acquiring input data, training a model using the input data, and applying the learnt model [24]. The simplest method to conceptualize model training is as an incremental learning process in which the model is exposed to fresh data at each stage [25]. The model generates predictions at each step and gets input on how well those projections worked out. The information is used to enhance future projections and make any required adjustments. If a model's parameters are altered in an effort to provide a more accurate forecast, it may reflect a previously accurate prediction incorrectly [26]. In parameter space, learning is therefore shown as a cyclic process. Training the model with a balance of exceptional prediction performance may need a large number of iterations [27]. When the model's predictions no longer become better, the procedure is over.

Table 1: Comparative Analysis of Different Prediction Models based on Machine Learning and Deep Learning

Prediction Models	Parameters	Objective	Tool	Outcomes
Matrix Factorization and Minimum Redundancy-Based Dual Regularized Unsupervised Feature Selection (DR-FS-MFMR) [1]	Accuracy and Normalized Mutual Information	removing unnecessary features from the original feature list	Python	Make use of a number of data points that are contained in the feature space.
Binary Bat Algorithm (BBA) with Greedy Crossover [2]	Accuracy and predictive gene features	excellent classification precision using few genes	Python	Average classification 95.85% accuracy using predictive gene features <1%
Graph Theoretic-based Gene Selection [3]	Accuracy (ACC), Matthews Correlation Coefficient (MCC), and execution time	To increase the relevance of selected genes having the target class to reduce the inner redundancy.	Weka	Genes to remove redundant and irrelevant genes and improve accuracy
The Markov Blanket ranking approach with Graph Neural Networks model (GAMB-GNN) [4]	accuracy and f1-score	To reduce redundancy among features	MATLAB	accuracy and f1-score improved by 3.98%–24.36% and 4.22%–31.93%
Minimum Redundancy Maximum Relevancy-Dragonfly Black Hole (MRMR-DBH) [5]	Accuracy	Decrease the complexity of the feature space while preserving a consistent set of genes that discriminate.	Weka	Accuracy more than 83.33%
Support vector machine (SVM) and metaheuristic algorithm [6]	Accuracy, AUC	minimizes the complexity of time and data dimensions	MATLAB	Improved Accuracy with certain AUC
KNN-Binary Harris Hawks Optimization [7]	Accuracy and Standard Deviation	less genes and get a high degree of classification precision	Weka	Improved Accuracy and Limited Standard Deviation
Machine Learning Techniques [8]	Accuracy	minimizing the redundancy and dependency	MATLAB	improve dimensionality reduction precision
Infiltration Tactics based Optimization algorithm (ITO) [10]	Training time and accuracy	Tor reduce redundancy	MATLAB	Improved time and accuracy

EfficientNet-B3 [11]	Receiver Operator Curve (ROC) area under the curves (AUCs)	To improve classification rate	Python	Improve Classification Rate

VI. PROPOSED WORK

The suggested work's algorithm is as follows:

Step 1: Data Preparation

(i) Data Collection: Gather medical image data relevant to the classification task (e.g., MRI, CT scans).

(ii) Data Preprocessing:

- Normalize the images to ensure they have the same scale.
- Optionally, apply techniques such as cropping, resizing, or augmentation to improve model training and performance.

Step 2: Feature Extraction with PCA

(i) Flatten Images: Convert each image from a matrix format into a vector format.

(ii) Apply PCA:

- Compute the covariance matrix of the entire image dataset.
- Extract the eigenvectors and eigenvalues of the covariance matrix.
- Select the top principal components that capture the majority of variance in the data.
- Transform the original image data into a lower-dimensional space using these principal components to reduce computational complexity and focus on the most informative features.

Step 3: Sequence Generation for RNN

Prepare Sequential Data: Depending on the approach, this could involve treating each principal component as a sequence element or structuring patches of images in a sequence for the RNN to process. The goal is to create a time-series-like data structure where spatial or temporal correlations between features are maintained.

Step 4: RNN Model Configuration

(i) Configure RNN Architecture:

- Define the number of layers and the type of RNN cells (e.g., basic RNN, LSTM, GRU) based on complexity and sequence length.
- Set up the network with input layers adjusted to the number of PCA features, hidden layers, and output layers designed for the classification task (e.g., binary or multi-class classification).

(ii) Hyperparameter Tuning: Choose parameters like learning rate, number of epochs, batch size, and dropout rate for regularization.

Step 5: Model Training

(i) Feed Sequences to RNN: Input the PCA-transformed data into the RNN.

(ii) Training Process:

- Perform forward propagation to compute predictions.
- Calculate loss using an appropriate loss function (e.g., cross-entropy loss for classification).
- Apply Backpropagation Through Time (BPTT) to update the weights in the network using an optimizer like Adam or SGD.

Step 6: Evaluation

(i) Model Evaluation:

- Use a separate validation set to evaluate the model's performance.
- Calculate accuracy, precision, recall, and F1-score to gauge effectiveness.

(ii) Error Analysis: Identify any patterns in misclassifications to refine the model and preprocessing steps.

Step 7: Model Deployment and Prediction

(i) Deployment: Deploy the trained model in a clinical setting to assist healthcare professionals.

(ii) Make Predictions: Use the model to classify new medical images, providing support in diagnostic processes.

VII. CONCLUSIONS

We have given a top to bottom examination of as of late delivered profound learning methods for imaging in medication. Ongoing advancements in profound learning frameworks might work on the exactness of clinical imaging determination. In any case, for profound figuring out how to outperform customary AI models, a significant measure of information is required. A deep learning-based system for medical image classification is presented, which uses image training for classification. In this sense, one of the most important needs of the modern world is diagnostics. This study aimed to evaluate and compare a number of prediction models utilized in the medical image processing domain. Computer-aided technology and reliable image analysis are the primary ways that medical professionals may become more productive. In the present day, it is essential to develop image processing techniques that assist physicians in a range of medical specialties. These techniques undoubtedly help detect illnesses before they have an impact on a person's health and may save lives. In an attempt to close this gap, computer vision researchers have spent the past several decades creating automated systems that can analyze medical pictures and use computers to make choices.

REFERENCES

[1] Saberi-Movahed F, Rostami M, Berahmand K, Karami S, Tiwari P, Oussalah M, Band SS, (2022). Dual regularized unsupervised feature selection based on matrix factorization and minimum redundancy with application in gene selection. Knowledge-Based Systems. Knowledge-Based Systems.

[2] Seetharaman A, Sundersingh AC, (2022). Gene selection and classification using correlation feature selection based binary bat algorithm with greedy crossover. Concurrency and Computation: Practice and Experience.

[3] Azadifar S, Rostami M, Berahmand K, Moradi P, Oussalah M, (2022). Graph-based relevancy-redundancy gene selection method for cancer diagnosis. Computers in Biology and Medicine.

[4] Zhang S, Xie W, Li W, Wang L, Feng C. (2022). GAMB-GNN: Graph Neural Networks learning from gene structure relations and Markov Blanket ranking for cancer classification in microarray data. Chemometrics and Intelligent Laboratory Systems.

[5] Pashaei E, Pashaei E. (2021). Gene selection using hybrid dragonfly black hole algorithm: A case study on RNA-seq COVID-19 data. Analytical Biochemistry.

[6] Tavasoli N, Rezaee K, Momenzadeh M, Sehhati M. (2021). An ensemble soft weighted gene selection-based approach and cancer classification using modified metaheuristic learning. Journal of Computational Design and Engineering.

[7] Khurma RA, Castillo PA, Sharieh A, Aljarah I. (2020). New Fitness Functions in Binary Harris Hawks Optimization for Gene Selection in Microarray Datasets. In IJCCI

[8] Abdulqader DM, Abdulazeez AM, Zeebaree DQ. (2020). Machine learning supervised algorithms of gene selection: A review. Machine Learning.

[9] Hartcher KM, Lum HK. (2020). Genetic selection of broilers and welfare consequences: a review. World's poultry science journal.

[10] Zahoor J, Zafar K. (2020). Classification of microarray gene expression data using an infiltration tactics optimization (ITO) algorithm. Computational Methods for the Analysis of Genomic Data and Biological Processes.

[11] Kanavati F, Toyokawa G, Momosaki S, Rambeau M, Kozuma Y, Shoji F, Yamazaki K, Takeo S, Iizuka O, Tsuneki M. (2020). Weakly-supervised learning for lung carcinoma classification using deep learning. Scientific reports.

[12] Elbashir MK, Ezz M, Mohammed M, Saloum SS. (2019). Lightweight convolutional neural network for breast cancer classification using RNA-seq gene expression data. IEEE Access.

[13] Bulusu, S., Sai Surya Siva Prasad, R., Telluri, P., & Neelima, N. (2021). Methods for epileptic seizure prediction using EEG signals: A survey. In Artificial Intelligence Techniques for Advanced Computing Applications: Proceedings of ICACT (pp. 101-115). Springer Singapore.

[14] Madan, K., Bhanu Anusha, K., Pavan Kalyan, P., & Neelima, N. (2019). Research on different classifiers for early detection of lung nodules. Int J Recent Technol Eng.

[15] H. P. Chan, L. M. Hadjiiski, and R. K. Samala. (2020). Computer-aided diagnosis in the era of deep learning. Medical Physics, vol. 47, no. 5, pp. e218–e227.

[16] F. Ritter, T. Boskamp, A. Homeyer et al. (2020). Medical image analysis. IEEE Pulse, vol. 2, no. 6, pp. 60–70.

[17] J. Ker, L. Wang, J. Rao, and T. Lim. (2017). Deep learning applications in medical image analysis. IEEE Access, vol. 6, pp. 9375–9389.

[18] M. Jena, S. P. Mishra, and D. Mishra. (2018). A survey on applications of machine learning techniques for medical image segmentation. International Journal of Engineering & Technology, vol. 7, no. 4, pp. 4489–4495.

[19] S. Niyas, S. J. Pawan, M. Anand Kumar, and J. Rajan. (2022). Medical image segmentation with 3D convolutional neural networks: a survey. Neurocomputing, vol. 493, pp. 397–413.

[20] P. Dutta, P. Upadhyay, M. De, and R. G. Khalkar. (2020). Medical image analysis using deep convolutional neural networks: CNN architectures and transfer learning. International Conference on Inventive Computation Technologies (ICICT), pp. 175–180.

[21] Rajendra, P., Kumari, M., Rani, S., Dogra, N., Boadh, R., Kumar, A., & Dahiya, M. (2022). Impact of artificial intelligence on civilization: Future perspectives. Materials Today: Proceedings, 56, 252–256. https://doi.org/10.1016/j.matpr.2022.01.113.

[22] M. Jogin, M. S. M. Mohana, G. D. Divya, R. K. Meghana, and S. Apoorva. (2018). Feature extraction using convolution neural networks (CNN) and deep learning. 3rd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), pp. 2319–2323.

[23] J. Goodfellow, J. Shlens, and C. Szegedy. (2014). Explaining and harnessing adversarial examples. https://arxiv.org/abs/1412.6572.

[24] Z. Hu, J. Tang, Z. Wang, K. Zhang, L. Zhang, and Q. Sun. (2018). Deep learning for image-based cancer detection and diagnosis − a survey. Pattern Recognition, vol. 83, pp. 134–149.

[25] X. Liu, L. Song, S. Liu, and Y. Zhang. (2021). A review of deep-learning-Based medical image segmentation methods. Sustainability, vol. 13, no. 3, p. 1224.

[26] Singhal, A., Phogat, M., Kumar, D., Kumar, A., Dahiya, M., & Shrivastava, V. K. (2022). Study of deep learning techniques for medical image analysis: A review. Materials Today: Proceedings, 56, 209–214. https://doi.org/10.1016/j.matpr.2022.01.071.

[27] Kalra, G., Rajoria, Y. K., Boadh, R., Rajendra, P., Pandey, P., Khatak, N., & Kumar, A. (2022). Study of fuzzy expert systems towards prediction and detection of fraud case in health care insurance. Materials Today: Proceedings, 56, 477–480. https://doi.org/10.1016/j.matpr.2022.02.157.