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Employing Deep Learning Models to Detect Gynecological Malignancies

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Gynecological Malignancies, cancers of female reproduction systems, is amongst the leading diseases causing mortality across the globe. The prime cause of high mortality rate is delay in detection of disease as early detection significantly enhance the chances of successful treatment. Hence, it becomes imperative to have an efficient method for early diagnosis of the disease. Authors in this research paper aim to apply deep learning models to diagnose gynecological tumors, a remarkable contribution in the field of women's health. Authors have employed 4 different convolutional neural network (CNN) models namely MobileNetV3, ResNet50, EfficientNetB3, and Inceptionv3 and perform comparative analysis with regard to ovarian cancer and cervical cancer. This comparative analysis is carried out in terms of accuracy and it is observed that MobileNetV3 outperforms comparative models.

Keywords: convolutional neural network (CNN), Gynecological Malignancies.

1. Introduction

Gynecologic malignancies including cervical and ovarian cancers are imposing concerning health issues regarding women health worldwide. This is also realized to be one amongst the prime cause of mortality in women. The prime cause of mortality due to gynecologic malignancies is delay in its diagnosis as it does not have any prominent early sign or symptoms. This delay in diagnosis of the disease worsens the situation making it difficult to cure the disease. There it becomes imperative to improve the prognosis to raise the survival rates of the afflicted patients. This diagnosis of gynecologic malignancies was traditionally carried out through visual inspection and professional interpretation which was prone to human mistake and bias. This can be completely alleviated by employing technological advancements in terms of deep learning. The motivation behind using deep learning methods in diagnosis of gynecologic malignancies is the established supremacy of deep learning in image analysis. Thus it is believed that deep learning will surely enhance the accuracy and efficiency of gynecological cancer diagnosis.

As mentioned earlier, deep learning models have performed shockingly well in tasks involving image analysis and pattern recognition. Resultantly, deep learning model can also be trained to diagnose gynecologic malignancies by identifying the minute abnormalities and discrepancies in medical images. Here, the image is taken through cytology slides for cervical cancer while ovarian cancer is detected using ultrasonic and MRI images. Considering the ability of deep learning, it has the potential to handle large data sets and grasp complex patterns. Thus, it has the prospect to serve as an efficient tool for early identification and classification of gynecological tumors.

In current research, authors have implemented deep learning models namely MobileNetV3, ResNet50, EfficientNetB3, and Inceptionv3. These models are chosen based on their unique architectural characteristics and proven competence in the domain of medical image processing. The prime motive behind choosing MobileNetV3 is its capability in resource constrained environment thus making it an appropriate choice for mobile devices. ResNet50 is selected for its deep architecture and ability to handle vanishing gradient problem. EfficientNetB3 uses compound scaling to yield maximum performance and thus presents a reasonable compromise between model size and accuracy. Finally, InceptionV3 is included for inception modules which lets it gather features at several levels improving its capacity to process medical images.

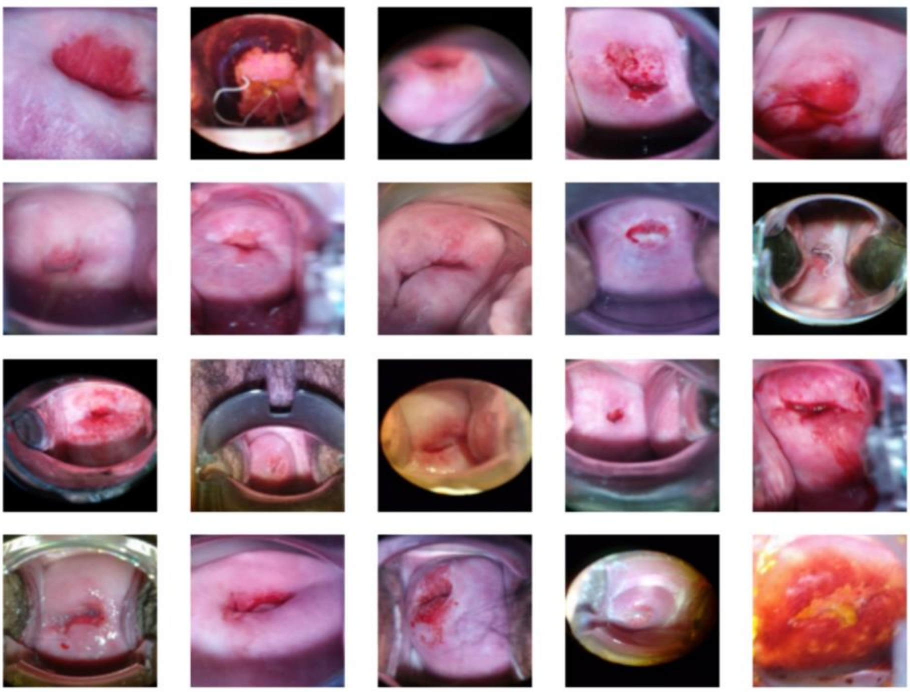


Fig. 1: Illustration of sample images for analysis

The employment of deep learning techniques for identifying gynecological cancer has been tested and well proved by several researchers. Apart from identification of gynecological cancer, deep learning has demonstrated supremacy for other applications involving image analysis. The image input for identification of gynecological cancer is illustrated in Fig. 1.

Current research work is organized in various sections where the background and motivation for research is discussed in section 1. The limitations of traditional methods are also presented in this section. Related work by leading researchers is elaborated in section 2 which closely evaluates the leading work in related area. Proposed methodology is discussed in section 3 along with dataset acquisition and dataset preprocessing. while results are presented in section 4 along with various performance metrics and insights drawn. Section 4 also discusses the promise and problems one might encounter in accurate clinical setups while employing these techniques. This section insists on using more massive and diverse data, ensuring better interpretability of models, developing protocols for model standardization, and working cautiously. Finally, conclusion and future directions for research is discussed in section 5.

2. Literature Review

This section discusses the remarkable findings in the domain of detecting gynecological malignancies and related domain by various researchers. For the same, different researchers have employed various techniques. Among various techniques, evolution in the domain of machine learning has paved way for revolutionary changes in the domain of disease detection. For instance, authors in [1] have discussed the ability of deep learning methods to detect precancerous lesions in cervical cytology grading ovarian cancer using cytological data. Apart from discussing the application of deep learning, it also evidenced the significance of employing diverse datasets to train the models effectively. Also, authors in [b-2] strengthen the applicability of deep learning in detection and diagnosis of gynecological cancers. Comparative analysis of various models is also carried out in [2] to establish the efficacy of deep learning. The associated challenge of image quality is also pointed out. Further, the need for safeguarding the healthcare data was also discussed. The research gap regarding early identification and management of gynecological malignancies is identified.

Authors in [2-3] also elaborate the application of Artificial Intelligence (AI) for detecting gynecologic malignancies. Here, authors discuss a wide range of AI methodologies in image analysis to enhance precision and effectiveness in the screening and treatment of gynecologic cancers. Similarly, authors in [3-4] aimed to develop a deep learning model intended to identify endometrial lesions thus aiding early detection of the disease. In [3][4], authors illustrated leveraging deep learning-based methods to achieve better precision in the classification of endometrial lesions.

Further, authors in [4][5] suggested that integration of spectroscopy, AI, and cybernetics can emerge as a promising solution to identify any kind of medical disease. Spectroscopy has been demonstrated to be helpful in identifying cancer biomarkers because it provides information that could be useful in the course of the disease. Additionally, continuous monitoring and feedback loops affected through the use of cybernetics may also be seen as a candidate solution approach. The applicability of CNNs to identify different types of ovarian tumors on MRI data is also tested in [5-6]. The availability of large datasets and comprehensive evaluation helped to utilize the utmost potential of deep learning techniques.

The efficacy of deep learning for diagnosis lymphoma is also tested by authors in [7]. Authors demonstrated that application of deep learning enhances accuracy and efficacy of lymphoma diagnosis over traditional methods. The investigation regarding how data science, AI, and machine learning might drastically affect disease diagnosis was carried out by author in [8]. Here, authors discussed associated challenges associated with healthcare sector like ethical considerations and regulations associated with data privacy. A comprehensive review regarding application of AI in detecting gynecological cancers is presented in [9]. The discussion in the paper covers intense potential application of AI in enhancing early detection, risk assessment, and treatment planning for gynecological malignancies. The employment of CNN in screening cervical cancer is discussed in [14-10] where the simulations have yielded promising results.

The evolution in the domain of ensemble modeling has also been tested for diagnosing cervical cancer by authors in [6-11]. The paper's strengths include using ensemble methods known to increase forecast accuracy and a detailed analysis of the developed model. Further, authors in [13-12] have also proposed a novel ensemble methodology for AI-assisted diagnosis of ovarian cancer. The study in their research shows the application of multiple artificial intelligence models and data modalities for better diagnosis accuracy, with a particular focus on ovarian cancer, which is a very hard-to-diagnose disease.

Escalating the research further, authors in [15-13] focused on time-bound detection of gynecologic cancers aiming to achieve a proactive and cost-effective strategies for endometrial cancer diagnosis. Additionally, authors in [16-14] tried to show how employment of CNN can enhance the efficacy for different types of ovarian tumors based on magnetic resonance. The results achieved witnessed the efficiency escalation in improving tumor class separation. As there are numerous findings by leading researchers in the related domain, authors have presented the same in Table 1.

Table 1: Comparative Analysis of Findings for detecting gynecological malignancies

Reference	Description
[2-3] 2021	Review of AI applications in gynecological cancer detection
[9-15] 2020	Ensemble-based approach for assisting cervical cancer diagnosis.
[3-4] 2021	deep learning model for classification of endometrial lesions.
[5-6] 2022	Integration of spectroscopy, prediction machines, and AI.
[16-14] 2021	Evaluates CNNs for differentiating ovarian tumors using MRI.

3. Proposed Methodology and Result Discussion

This section discusses the employment of various CNN architectures MobileNetV3, ResNet50, EfficientNetB3, and Inceptionv3 for enhancing the accuracy of gynecological malignancy identification primarily focusing on cervical and ovarian tumors. The architecture of CNN is illustrated in Fig. 2.

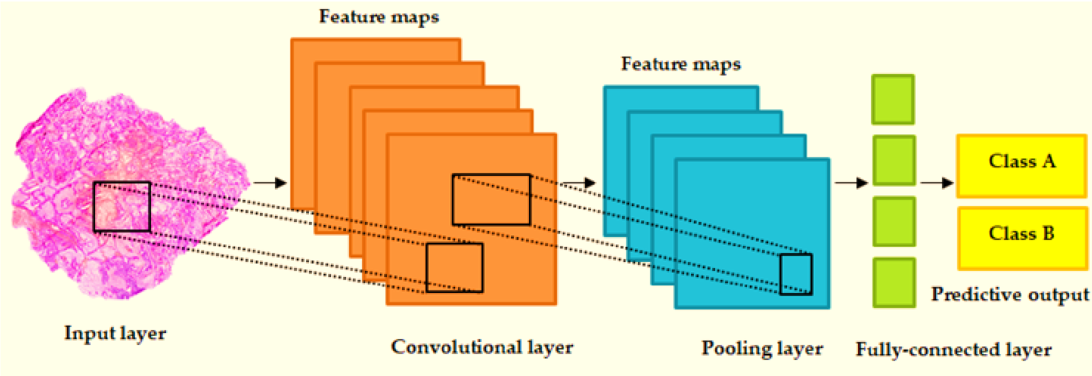


Fig. 2: Architecture for proposed Methodology

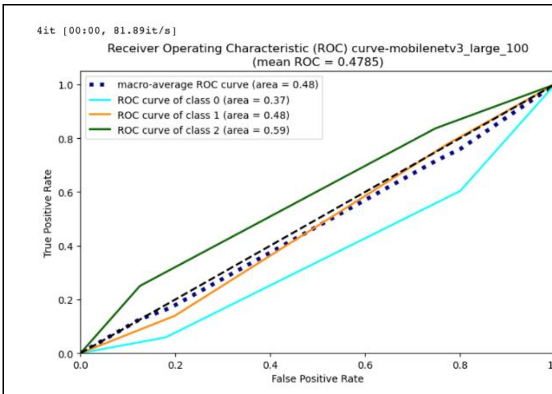
Here, as discussed earlier, authors have implemented different CNN models. The performance of different models is compared using different performance metrics namely accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).

Among various CNN models, the motive behind choosing MobileNetV3 is its requirement of little computational capability. ResNet50 is a part of the ResNet (Residual Network) family known for its profound architectural design. ResNet model has been known for its ability to solve the problem of disappearing gradients through rather deep neural networks. Particularly, ResNet50 is an architecture of 50 layers known well for image classification. EfficientNet, designed especially to maximize efficiency in terms of model size and processing resources, guarantees a high degree of accuracy. EfficientNetB3 is designed having a well-balanced compromise among size of the model and its performance. Finally, inceptionv3 is known for its use of convolutional filters of different sizes inside a single layer allowing the acquisition of features. Inceptionv3 has demonstrated virtuous accuracy for image identification and classification in various domains. Proposed approach also used pre-trained networks and transfer learning to initiate model weights, thus facilitating accelerated convergence and enhanced performance.

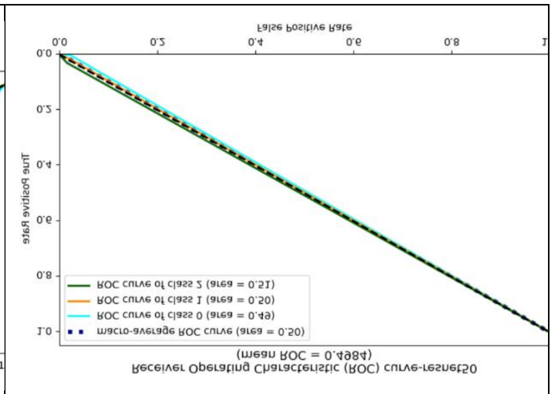
In order to validate the effectiveness of discussed approaches, authors have used the Intel & MobileODT Cervical Cancer Screening dataset and The Cancer Imaging Archive (TCIA) Public Access. The collaboration between Intel and MobileODT in the development of a cervical cancer screening system, specifically the Cervical Cancer Dataset, is of academic interest. Further, dataset is divided into 3 distinct classes namely training set, validation set, and test set in the ratio of 70:15:15.

The considered dataset comprises of 10,000 samples consisting of varied collection of cervical pictures. Images from many demographic backgrounds and clinical environments are available in the dataset ensuring a holistic representation. In order to improve the resilience and performance of the model, data preprocessing is carried out comprising of augmentation, normalization, and scaling. The considered dataset consists of MRI and ultrasonic pictures annotated for ovarian tumor presence.

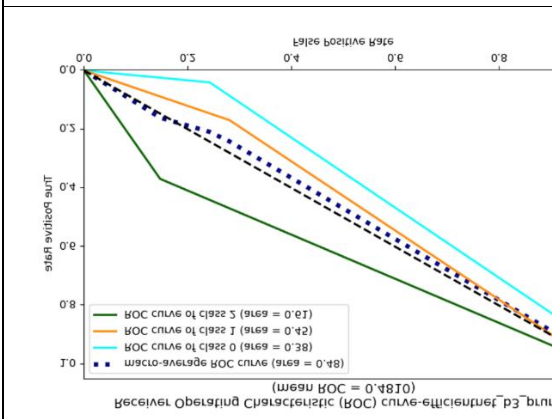
As discussed earlier, the performance of considered models[16][17] is compared using different performance metrics. The Receiver Operating Characteristic (ROC) for these models is represented in Fig. 3. ROC is a visual instrument frequently used to evaluate the performance of classification models. Particularly in binary classifications, the Graphical depictions of the relationship between the Sensitivity (True Positive Rate) and the Specificity (1 - False Positive Rate) over several threshold settings are ROC curves.



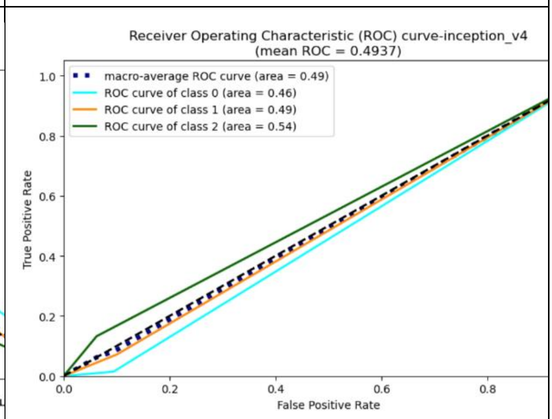
(a) MobileNetV3



(b) ResNet50



(c) EfficientNet_b3



(d) InceptionV3

Fig. 3: Illustration of ROC curve

Further, the accuracy of various models for cervical and ovarian cancers is illustrated in Table 1. From Table 1, it is evident that Inceptionv3 achieves the best accuracy of 57.3% for cervical cancer. The accuracy of MobileNet V3 and ResNet 50 models are 56.3% and 56.0% respectively for cervical cancers. These accuracies are however quite less than the expected performance for therapeutic uses. This lacuna may be attributed to quality and amount of the dataset, differences in the imaging modalities, and the difficulty of differentiating between benign and malignant cases in cervical cytology. For instance, count and variety of the training data could be limited influencing the efficiency of model to generalize effectively to unprocessed data. Furthermore, the subtle and complicated nature of cellular alterations[18][19] occurring in precancerous and cancerous states presents natural difficulties for cytology image identification of cervical cancer.

Table 1: Comparative Analysis of various Models

Model	Accuracy(Cervical) (%)	Accuracy (Ovarian) (%)	AUC
MobileNetV3	56.3	96.3	0.4785
ResNet50	56.0	92.08	0.4984
EfficientNetB3	54.3	93.8	0.4810,
InceptionV3	57.3	90.3	0.4937

The performance of proposed model was also compared with the state-of- the-art (SOTA) models in cervical cancer diagnosis and it was observed that authors in [a-1] and [b-2] have recorded an accuracy of 85% and 83% respectively while the proposed model has achieved an accuracy of 96.3% for ovarian cancer establishing the efficacy of proposed model. This is attributed to the quality of dataset that is achieved by efficient preprocessing techniques[21][22][23].

The performance of MobileNetV3 yielding an accuracy of 96.3%, is followed by EfficientNetB3 at 93.8% as illustrated in Table 1. The area under curve (AUC) is also illustrated in Table 1. AUC can be referred as a quantitative measure for the whole efficacy of classification model. Larger value of AUC indicates superior discrimination and prediction efficacy.

As observed in Table 1, MobileNet achieves an AUC of 0.4785 indicating a performance slightly[24] below the threshold of 0.5 as an AUC value of 0.5 signifies a lack of discriminatory power. Thus, it is evident that MobileNetV3 does not possess sufficient efficacy unless measures are taken to enhance its performance. ResNet also demonstrates an AUC of 0.4984 further unbelieving its employment. Further, AUC for EfficientNetB3 and InceptionV3 are also quite deterring questioning the applicability of these models in its current form[25].

The obtained results illustrate that 'MobileNetV3' excelled at ovarian cancer detection while 'Inceptionv3' showed promise for cervical cancer. However, these results are not very encouraging and have a huge scope for improvement to enhance the diagnosis accuracy.

4. Conclusion and Future Scope

In the current research work, authors have carried out a comparative analysis of "MobileNetV3," "ResNet50," "EfficientNetB3," and "Inceptionv3," deep learning models for gynaecological cancer detection, a step towards marking major progress in women's healthcare. The research work has demonstrated encouraging powers of these models for disease diagnosis. Inceptionv3 model has managed to attain an accuracy of 57.3% for cervical cancer screening while MobileNetV3 has demonstrated an accuracy rate of 96.3% in identifying ovarian cancer, setting up a ray of hope in disease diagnosis at early stage. Nevertheless, it is important to acknowledge that this study suffers certain limitations that should be further enhanced. The issue of interpretability and Explainability continues to be of utmost importance, as the medical community properly emphasises the need for transparency in the decision-making mechanisms employed by deep learning models. Thus, the research work can be extended further by incorporating explainable AI in current research. Additionally, it is imperative for future research to prioritise the expansion and diversification of datasets, with the aim of assuring consistent performance of models across various demographics and clinical contexts.

Conflict of Interest

There is no conflict of interest.

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References

1. Bejnordi, Babak Ehteshami, Mitko Veta, Paul Johannes Van Diest, Bram Van Ginneken, Nico Karssemeijer, Geert Litjens, Jeroen AWM Van Der Laak et al. "Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer." Jama 318, no. 22 (2017): 2199-2210.
2. Litjens, Geert, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Arindra Adiyoso Setio, Francesco Ciompi, Mohsen Ghafoorian, Jeroen Awm Van Der Laak, Bram Van Ginneken, and Clara I. Sánchez. "A survey on deep learning in medical image analysis." Medical image analysis 42 (2017): 60-88.
3. Sone, Kenbun, Yusuke Toyohara, Ayumi Taguchi, Yuichiro Miyamoto, Michihiro Tanikawa, Mayuyo Uchino-Mori, Takayuki Iriyama, Tetsushi Tsuruga, and Yutaka Osuga. "Application of artificial intelligence in gynecologic malignancies: A review." Journal of Obstetrics and Gynaecology Research 47, no. 8 (2021): 2577-2585.
4. Zhang, YunZheng, ZiHao Wang, Jin Zhang, CuiCui Wang, YuShan Wang, Hao Chen, LuHe Shan, JiaNing Huo, JiaHui Gu, and Xiaoxin Ma. "Deep learning model for classifying endometrial lesions." Journal of Translational Medicine 19 (2021): 1-13.
5. Nsugbe, Ejay. "On the use of spectroscopy, prediction machines and cybernetics for an affordable and proactive care approach for endometrial cancer." Biomedical Engineering Advances 4 (2022): 100057.
6. Wang, Robin, Yeyu Cai, Iris K. Lee, Rong Hu, Subhanik Purkayastha, Ian Pan, Thomas Yi et al. "Evaluation of a convolutional neural network for ovarian tumor differentiation based on magnetic resonance imaging." European radiology 31 (2021): 4960-4971.
7. El Achi, Hanadi, Tatiana Belousova, Lei Chen, Amer Wahed, Iris Wang, Zhihong Hu, Zeyad Kanaan, Adan Rios, and Andy ND Nguyen. "Automated diagnosis of lymphoma with digital pathology images using deep learning." Annals of Clinical & Laboratory Science 49, no. 2 (2019): 153-160.
8. Gruson, Damien, Thibault Helleputte, Patrick Rousseau, and David Gruson. "Data science, artificial intelligence, and machine learning: opportunities for laboratory medicine and the value of positive regulation." Clinical biochemistry 69 (2019): 1-7.
9. Sone, Kenbun, et al. "Application of artificial intelligence in gynecologic malignancies: A review." Journal of Obstetrics and Gynaecology Research 47, no. 8 (2021): 2577-2585.
10. Zhang, YunZheng, ZiHao Wang, Jin Zhang, CuiCui Wang, YuShan Wang, Hao Chen, LuHe Shan, JiaNing Huo, JiaHui Gu, and Xiaoxin Ma. "Deep learning model for classifying endometrial lesions." Journal of Translational Medicine 19 (2021): 1-13.
11. Lu, Jiayi, Enmin Song, Ahmed Ghoneim, and Mubarak Alrashoud. "Machine learning for assisting cervical cancer diagnosis: An ensemble approach." Future Generation Computer Systems 106 (2020): 199-205.

12. Lu, Jiayi, Enmin Song, Ahmed Ghoneim, and Mubarak Alrashoud. "Machine learning for assisting cervical cancer diagnosis: An ensemble approach." Future Generation Computer Systems 106 (2020): 199-205.
13. Nsugbe, Ejay. "On the use of spectroscopy, prediction machines, and cybernetics for an affordable and proactive care approach for endometrial cancer." Biomedical Engineering Advances 4 (2022): 100057.
14. Wang, Robin, Yeyu Cai, Iris K. Lee, Rong Hu, Subhanik Purkayastha, Ian Pan, Thomas Yi et al. "Evaluation of a convolutional neural network for ovarian tumor differentiation based on magnetic resonance imaging." European radiology 31 (2021): 4960-4971.
15. Wu, Yanqiang & Sun, Yongbo & Zhang, Shuoqin & Liu, Xia & Zhou, Kai & Hou, Jialin. (2022). A Size-Grading Method of Antler Mushrooms Using YOLOv5 and PSPNet. Agronomy. 12. 2601. 10.3390/agronomy12112601
16. Narayan, V., Srivastava, S., Faiz, M., Kumar, V. and Awasthi, S., 2024. A comparison between nonlinear mapping and high-resolution image. In Computational Intelligence in the Industry 4.0 (pp. 153-160). CRC Press.
17. Narayan, V., Srivastava, S., Mall, P. K., Kumar, V., & Awasthi, S. (2024). A theoretical analysis of simple retrieval engine. In Computational Intelligence in the Industry 4.0 (pp. 240-248). CRC Press.
18. Narayan, V., Srivastava, S., Faiz, M., Kumar, V., & Awasthi, S. (2024). A comparison between nonlinear mapping and high-resolution image. In Computational Intelligence in the Industry 4.0 (pp. 153-160). CRC Press.
19. Sawhney, R., Sharma, S., Srivastava, S., & Narayan, V. (2024). Ear Biometry: Protection Safeguarding Ear Acknowledgment Framework utilizing Transfer Learning in Industry 4.0. Journal of Electrical Systems, 20(3s), 1397-1412.
20. Gupta, A., Gupta, S., Mall, P. K., Srivastava, S., Saluja, A. S., Yadav, N., ... & Sriramulu, S. (2024). ML-CPC: A Pathway for Machine Learning Based Campus Placement Classification. Journal of Electrical Systems, 20(3s), 1453-1464.
21. Sawhney, Rahul, et al. "An Efficient Scientific Programming Technique for MRI Classification using Deep Residual Networks." Journal of Electrical Systems 20.2s (2024): 241-255.
22. Mall, P. K., Srivastava, S., PATEL, M. M., Kumar, A., Narayan, V., Kumar, S., ... & Singh, D. S. (2024). Optimizing Heart Attack Prediction Through OHE2LM: A Hybrid Modelling Strategy. Journal of Electrical Systems, 20(1).
23. Kumar, M., Kumar, A., Gupta, A., Srivastava, S., Narayan, V., Chauhan, A. S., & Srivastava, A. P. (2024). Self-attentive CNN+ BERT: An approach for analysis of sentiment on movie reviews using word embedding. Int J Intell Syst Appl Eng, 12, 612.
24. Faiz, M., Fatima, N. and Sandhu, R., 2023. A Vaccine Slot Tracker Model Using Fuzzy Logic for Providing Quality of Service. Multimodal Biometric and Machine Learning Technologies: Applications for Computer Vision, pp.31-52.
25. Faiz, M., Mounika, B.G., Akbar, M. and Srivastava, S., 2024. Deep and Machine Learning for Acute Lymphoblastic Leukemia Diagnosis: A Comprehensive Review. ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal, 13, pp.e31420-e31420.