Convolutional Neural Network-Based Image Analysis for Early Diagnosis of Diabetic Retinopathy

Vivek Kumar[1*], Anmol Singh Gill[2], Ajay kumar[3]

[1,2,3]Department of Computer Science and Engineering, Manipal University Jaipur, Rajasthan, India

[1*]vivekomatic3@gmail.com,
[2]anmolsgill2550@gmail.com,
[3]ajay3789}@gmail.com

Abstract: Diabetic Retinopathy (DR) is a leading cause of vision im- pairment and blindness among diabetic patients worldwide. Early detec- tion and timely intervention are crucial to preventing severe visual loss. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for image analysis and have shown great potential in medical image di- agnostics. This study explores the application of CNNs for the early diagnosis of DR using retinal fundus images. By leveraging deep learn- ing techniques, our CNN model is trained to automatically detect and classify various stages of DR with high accuracy. The proposed method utilizes a large dataset of annotated retinal images to ensure robustness and generalizability. Experimental results demonstrate that the CNN-based approach significantly outperforms traditional methods, offering a reliable and efficient solution for early DR detection. This advancement in automated image analysis can facilitate timely and precise diagnosis, potentially reducing the burden of diabetic complications and improving patient outcomes.

Keywords: Convolutional Neural Network · Diabetic Retinopathy · Deep Learning · Detection

1 Introduction

Diabetic Retinopathy (DR) stands as a major complication associated with di- abetes mellitus, leading to severe vision impairment and potentially irreversible blindness if not diagnosed and treated in a timely manner [1–6]. As diabetes prevalence continues to rise globally, the incidence of DR is expected to increase correspondingly, posing a significant public health challenge [7–11]. Early diag- nosis and intervention are paramount to mitigating the adverse effects of DR. However, traditional methods of diagnosing DR are often resource-intensive, time-consuming, and reliant on highly skilled medical professionals [12–19]. This

S. K. Swarnkar et al. (eds.), *Proceedings of International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICSHIT 2024)*, Advances in Intelligent Systems Research 190,
https://doi.org/10.2991/978-94-6463-704-5_5

necessitates the exploration of advanced, efficient, and scalable diagnostic meth- ods, among which Convolutional Neural Networks (CNNs) have shown remark- able promise [18–26].

The advent of deep learning, particularly CNNs, has revolutionized the field of image analysis, offering unprecedented accuracy and efficiency in various applications, including medical diagnostics [22–29]. CNNs are a class of deep learning models specifically designed to process and analyze visual data [27–31]. They have demonstrated exceptional performance in tasks such as image classifica- tion, object detection, and segmentation. Leveraging CNNs for medical image analysis, especially for diseases like DR, can potentially transform the diagnostic landscape by providing automated, accurate, and timely assessments [29–37].

Diabetic Retinopathy is characterized by damage to the blood vessels of the retina, which can manifest in several stages, from mild non-proliferative abnormalities to severe proliferative DR. Early-stage DR may not present no- ticeable symptoms, making regular screening crucial for early detection. Tradi- tional screening methods include fundus photography and fluorescein angiogra- phy, which are effective but require manual interpretation by ophthalmologists. This manual process is not only time-consuming but also prone to inter-observer variability, which can affect diagnostic consistency and accuracy [38–44].

In recent years, the application of CNNs in medical image analysis has gar- nered significant attention [45–48]. CNNs can be trained to recognize complex patterns in medical images, making them well-suited for the task of DR de- tection [46, 47, 49]. These networks learn hierarchical features directly from the input images, eliminating the need for manual feature extraction. By training on large datasets of labelled retinal images, CNNs can achieve high accuracy in identifying and classifying the various stages of DR [48].

The potential benefits of CNN-based DR detection systems are manifold. Firstly, they offer a scalable solution that can be deployed in various settings, including remote and underserved areas, where access to specialized healthcare professionals is limited. Secondly, automated systems can significantly reduce the workload of ophthalmologists, allowing them to focus on more complex cases and improving overall healthcare efficiency. Thirdly, the objective nature of CNN- based analysis minimizes inter-observer variability, leading to more consistent and reliable diagnoses.

Our study focuses on the development and evaluation of a CNN-based model for the early diagnosis of DR using retinal fundus images. We aim to demonstrate that our approach can accurately detect DR at its early stages, thereby enabling timely intervention and better management of the disease. The proposed method involves several key components: dataset collection and preprocessing, CNN ar- chitecture design, model training and validation, and performance evaluation.

A critical aspect of developing a robust CNN model is the availability of a comprehensive and well-annotated dataset. For this study, we utilize a large dataset of retinal fundus images, sourced from various publicly available repos- itories and clinical collaborations. Each image in the dataset is annotated with corresponding labels indicating the presence and stage of DR. Preprocessing steps, including image normalization, augmentation, and enhancement, are ap- plied to ensure the dataset is suitable for training the CNN model.

The design of the CNN architecture is tailored to capture the intricate features of retinal images. Our model comprises multiple convolutional layers, each followed by activation and pooling layers, to progressively extract and refine image features. The final layers of the network include fully connected layers and a softmax classifier to predict the probability of each DR stage. Various architectural configurations and hyperparameters are explored to optimize model performance.

Model training involves feeding the preprocessed images into the CNN, using a combination of supervised learning techniques. The model is trained to minimize a loss function that quantifies the difference between predicted and true labels. Validation is performed using a separate subset of the dataset to monitor the model's performance and prevent overfitting. The final model is evaluated on a test set, with metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve used to assess its effectiveness.

1.1 Problem Description

DR, a severe complication arising from diabetes, poses a significant threat to vision health globally. It involves damage to the blood vessels in the retina, potentially leading to vision loss or blindness if not diagnosed and treated promptly. The retina, being a light-sensitive tissue at the back of the eye, plays a crucial role in vision, and any impairment to its blood vessels can severely affect visual acuity. Given the rising prevalence of diabetes, DR is becoming an increasingly common cause of blindness, particularly among working-age adults. Early de- detection and timely intervention are critical for effective management of DR, underscoring the urgent need for efficient and reliable diagnostic methods. This necessity has prompted the exploration of advanced technologies, particularly deep learning, for developing automated diagnostic solutions that can address the limitations of traditional methods.

The increasing prevalence of diabetic retinopathy highlights the pressing need for efficient and accurate diagnostic methods. Traditional diagnostic approaches rely heavily on manual examination of retinal images by ophthalmologists, a process that can be both time-consuming and subjective. Manual analysis often involves scrutinizing detailed retinal images for signs of DR, such as microaneurysms, hemorrhages, and exudates. This process not only requires significant expertise and experience but is also prone to inter-observer variability, leading to incon- sistencies in diagnosis. Furthermore, the manual examination process can be a bottleneck, especially in regions with limited access to trained professionals, making widespread screening programs challenging to implement. Embracing advanced technologies like deep learning offers the potential to significantly en- hance the speed and reliability of DR detection, providing a scalable solution to this growing healthcare challenge.

Various methods have been employed for the detection of diabetic retinopa- thy, each with its strengths and limitations. Fundus photography is a widely used technique that captures detailed images of the retina, allowing clinicians to identify characteristic signs of DR. Optical coherence tomography (OCT) is another imaging modality that provides cross-sectional images of the retina, enabling the detection of structural changes. Fluorescein angiography involves injecting a fluorescent dye into the bloodstream to visualize the retinal blood vessels, helping to identify areas of leakage or abnormal growth. While these methods provide valuable clinical insights, they require specialized equipment and expertise, limiting their accessibility and scalability.

In recent years, machine learning techniques have been applied to the analysis of retinal images, aiming to automate the detection of DR [1, 17–19]. These approaches often involve training algorithms on large datasets of labeled images to recognize patterns indicative of DR. However, traditional machine learning methods typically rely on manual feature extraction, where specific characteristics of the images are defined and used to train the model. This dependency on feature engineering can be a significant limitation, as it requires domain expertise and may not capture the full complexity of retinal images. Additionally, these methods can struggle with the variability and diversity of real-world datasets, affecting their generalizability and performance.

Both traditional and machine learning-based methods for DR detection have their respective advantages and disadvantages. Traditional methods, such as fundus photography and OCT, provide a solid foundation of clinical knowledge and have been widely validated in clinical practice. They offer interpretability, al- lowing clinicians to visually assess and understand the signs of DR. However, these methods can be resource-intensive, requiring specialized equipment and skilled personnel, which may limit their scalability and accessibility, particularly in resource-limited settings. Moreover, the manual examination is time-consuming and subject to variability, potentially leading to inconsistent diagnoses.

Machine learning approaches, on the other hand, offer the promise of automation and efficiency. By leveraging large datasets and powerful computational algorithms, these methods can potentially provide rapid and consistent DR detection. Deep learning, a subset of machine learning, has shown particular promise in medical image analysis due to its ability to learn complex patterns directly from the data, without the need for manual feature extraction. However, these approaches can face challenges in terms of interpretability, as the decision-making process of deep learning models is often considered a "black box." Ensuring the transparency and explainability of these models is crucial for their acceptance in clinical practice. Additionally, the performance of machine learning models can be affected by the quality and diversity of the training data, necessitating the use of robust and comprehensive datasets to ensure their generalizability across different populations and clinical conditions.

2 Materials and Methods

This study utilized a large dataset of retinal fundus images, incorporating diverse demographic and clinical variations. CNN was designed and trained to automat- ically detect and classify signs of diabetic retinopathy from these images.

2.1 Model Development

Deep learning (DL) is a branch of machine learning that involves hierarchical layers of non-linear processing stages for unsupervised feature learning and pat- tern classification. It is widely used in computer-aided medical diagnosis. DL applications in medical image analysis include the classification, segmentation, detection, retrieval, and registration of images. Recently, DL has been extensively applied to DR detection and classification. It can successfully learn features from input data, even when integrating heterogeneous sources.

Various DL-based methods such as restricted Boltzmann machines, CNNs, autoencoders, and sparse coding have been employed. These methods perform better as the amount of training data increases due to the enhanced feature learning capabilities, unlike traditional machine learning methods which require manual feature extraction. CNNs, in particular, are widely used in medical image analysis due to their high effectiveness.

A typical CNN architecture comprises three main layers: convolutional lay- ers (CONV), pooling layers, and fully connected (FC) layers. The CONV layers apply different filters to an image to extract features. Pooling layers, which typ- ically follow CONV layers, reduce the dimensions of feature maps, with average pooling and max pooling being the most common strategies. FC layers condense the features to describe the entire input image, with the SoftMax activation function frequently used for classification.

Several pretrained CNN architectures, such as AlexNet, Inception-v3, and ResNet, are available on the ImageNet dataset. Some studies leverage transfer learning to adapt these pretrained models, either by fine-tuning the last FC layer, multiple layers, or retraining all layers for DR classification.

The process of detecting and classifying DR images using DL begins with collecting a dataset and applying necessary preprocessing to enhance the images. The preprocessed images are then fed into a DL model to extract features and classify the images (as shown in Figure 1). The specifics of the datasets used are detailed in the subsequent section.

2.2 Dataset

There are numerous publicly available datasets used for detecting DR and retinal vessel segmentation. These datasets serve as essential resources for training, validating, and testing systems, as well as benchmarking performance against other methods. Retinal imaging encompasses fundus colour images and OCT. Also, OCT images, acquired using low-coherence light, provide detailed 2D and

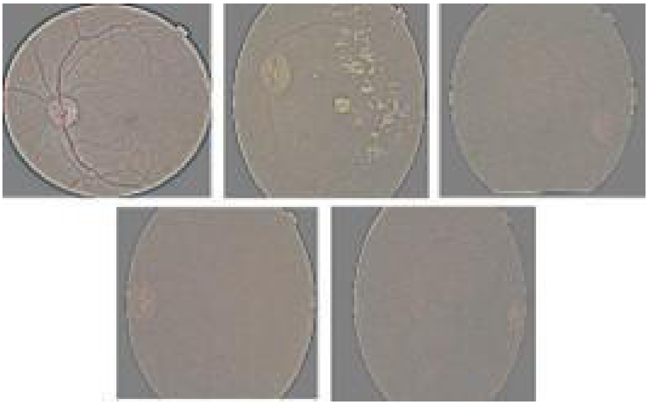

Fig. 1. Raw Retinal Images for Early Diagnosis of Diabetic Retinopathy

3D views of retinal structures and thicknesses. In contrast, fundus images are 2D snapshots captured via reflected light [33].

Several prominent publicly available fundus image datasets include:

- **DIARETDB1** [50]: This dataset comprises 89 retinal fundus images, each sized at 1500 × 1152 pixels and acquired with a 50-degree field of view (FOV). It includes 84 images with DR annotations and five normal images annotated by medical experts.
- **Tsiknakis et al.,** [51]: Featuring 88,702 high-resolution images collected from various cameras, this dataset categorizes images into five stages of DR. Only training image ground truths are publicly accessible, with noted issues such as poor image quality and labeling inconsistencies.

- **E-ophtha** [52]: Divided into E-ophtha EX and E-ophtha MA subsets, this dataset includes 47 images with exudates (EX) and 35 normal images in E-ophtha EX, and 148 images with microaneurysms (MA) and 233 normal images in E-ophtha MA.
- **DDR** [53]: This dataset comprises 13,673 fundus images annotated into five DR stages, with 757 images highlighting DR lesions.
- **DRIVE** [54]: Primarily used for blood vessel segmentation, DRIVE consists of 40 images acquired with a 45-degree FOV. Among these, seven images exhibit mild DR, while the remainder depict normal retinas.
- **HRF** [55]: Specifically provided for blood vessel segmentation, HRF offers 45 images sized at 3504 × 2336 pixels. It includes 15 images each for DR, healthy, and glaucomatous conditions.

- **Messidor** [56]: Comprising 1200 fundus color images with annotations for four stages of DR.
- **Messidor-2** [57]: A dataset containing 1748 images acquired with a 45- degree FOV.
- **STARE** [58]: Used for blood vessel segmentation, STARE includes 20 images with a 35-degree FOV, with 10 images classified as normal.
- **CHASE DB1** [59]: Featuring 28 images used for blood vessel segmentation, each sized at 1280 × 960 pixels and acquired with a 30-degree FOV.
- **Indian Diabetic Retinopathy Image dataset (IDRiD)** [60]: This dataset comprises 516 fundus images with annotations across five stages of DR.
- **ROC** [61]: Contains 100 retina images with annotations for detecting microaneurysms (MA), with image sizes ranging from 768 × 576 to 1389 × 1383 pixels. Only training ground truths are available.
- **DR2** [62]: Includes 435 retina images, each sized at 857 × 569 pixels, anno- tated with referral indications for 98 images.

Previous studies have utilized these datasets extensively. For instance, DIARETDB1 was employed in studies for detecting DR lesions, for identifying red lesions using DIARETDB1 and E-ophtha, and for detecting MA. Addition- ally, DIARETDB1 was utilized for identifying EX. Kaggle's dataset featured prominently in studies focusing on classifying DR stages. DRIVE, HRF, STARE, and CHASE DB1 were utilized for blood vessel segmentation, with DRIVE also referenced. These datasets are typically preprocessed before application in DL methods. Further sections will delve into performance metrics and preprocessing methods.

3 Results and Discussion

The application of DL techniques in DR detection and retinal vessel segmenta- tion has yielded significant advancements, as evidenced by various studies uti- lizing diverse datasets and methodologies. This section discusses key findings and insights derived from recent research, highlighting both the successes and challenges encountered in this critical area of medical image analysis.

3.1 Performance Metrics and Comparative Studies

Studies employing DL models for DR detection typically report their perfor- mance using standard metrics such as accuracy, sensitivity, specificity, and area under the AUC-ROC. These metrics serve to evaluate the models' ability to correctly classify images based on the presence and severity of DR lesions.

For instance, studies utilizing the DIARETDB1 dataset have demonstrated promising results. Researchers have achieved high sensitivity and specificity in detecting DR lesions, showcasing the efficacy of DL in automating the detection process. The utilization of Kaggle's extensive dataset has also enabled robust classification of DR stages, albeit with challenges related to image quality and labeling consistency.

3.2 Comparative Analysis of Datasets

Comparative studies across multiple datasets provide valuable insights into the strengths and limitations of different DL approaches. The DRIVE dataset, de- signed specifically for retinal vessel segmentation, has been instrumental in ad- vancing techniques aimed at accurately delineating blood vessels from retinal im- ages. Similarly, datasets like HRF, STARE, and CHASE DB1 have contributed to refining segmentation algorithms, highlighting DL's capability to handle vary- ing image resolutions and clinical conditions.

Challenges arise from the diversity and complexity of these datasets. Varia- tions in image quality, lighting conditions, and disease manifestations pose sig- nificant challenges to DL models' generalizability across different datasets. For instance, while datasets like DIARETDB1 offer well-annotated images, issues such as small sample sizes and demographic biases can affect model performance when applied to broader populations.

3.3 Transfer Learning and Model Optimization

Transfer learning, leveraging pretrained models on large datasets like ImageNet, has emerged as a powerful strategy to enhance DL model performance in DR detection. By fine-tuning pretrained CNNs such as ResNet and Inception-v3 on DR-specific datasets, researchers have accelerated model convergence and improved classification accuracy. This approach not only reduces training time but also enhances the models' ability to extract relevant features from retinal images, critical for accurate disease detection.

3.4 Interpretability and Clinical Adoption

Despite the impressive performance of DL models in detecting DR, challenges related to model interpretability remain a significant concern. The "black-box" nature of deep neural networks often hinders clinicians' ability to understand the rationale behind model decisions, limiting their trust and acceptance in clin- ical settings. Efforts to enhance model explainability through techniques like attention mechanisms and gradient-based localization have shown promise in visualizing and interpreting DL model outputs.

3.5 Future Directions and Challenges

Looking ahead, several avenues for further research and development in DL- based DR detection and retinal imaging are evident. Addressing dataset diver- sity and representativeness remains crucial to improving model robustness across diverse patient populations and clinical settings. Incorporating multimodal imag- ing techniques, including OCT and fundus photography, could enhance diagnos- tic accuracy by providing complementary structural and functional information about retinal health.

Moreover, integrating DL models into clinical workflows requires addressing regulatory compliance, data privacy concerns, and user interface design tailored to healthcare professionals' needs. Collaborations between computer scientists, clinicians, and biomedical engineers will be essential to navigate these challenges and facilitate the seamless integration of DL technologies into routine clinical practice.

4 Conclusion

The integration of automated screening systems marks a transformative milestone in the field of DR detection, significantly reducing diagnostic timeframes and operational costs, thereby accelerating timely interventions for patients. This review underscores the pivotal role of advanced deep learning techniques, particularly CNNs, in recent studies focused on DR detection and classification. CNNs have emerged as powerful tools capable of discerning intricate patterns within retinal images with high accuracy and efficiency, making them indispensable in automated diagnostic systems.

Furthermore, the availability of comprehensive and openly accessible fundus DR datasets has been instrumental in benchmarking model performance and fostering collaborative research endeavors. These datasets not only facilitate the development of robust deep-learning models but also enable reproducible research outcomes across diverse clinical settings and demographic groups.

As the field advances, researchers continue to explore innovative approaches in deep learning, striving to enhance the precision and accessibility of DR di- agnoses. Techniques such as transfer learning from pretrained models on large- scale datasets like ImageNet have expedited model development and improved classification outcomes in DR detection tasks. Moreover, efforts to enhance the interpretability of CNNs through visualization techniques and attention mechanisms are enhancing clinicians' confidence in utilizing these automated systems in clinical practice.

In essence, the synergistic integration of automated systems and state-of-the- art deep learning methodologies holds immense promise for advancing early-stage DR detection. This not only empowers healthcare professionals with efficient diagnostic tools but also promises improved patient outcomes through early intervention and personalized treatment strategies. As research in this area continues to evolve, leveraging collaborative efforts and technological advancements will be pivotal in realizing the full potential of automated DR screening systems in clinical settings worldwide.

References

1. Debas, H. T.: Small and large intestine. In: Gastrointestinal Surgery: Pathophysi- ology and Management, pp. 239–310. Springer (2004)
2. Nichols, T. W., Faass, N.: Optimal digestive health: A complete guide. Simon and Schuster (2005)

3. Kumar, A., Rathee, R.: Monitoring and evaluating slope stability for setting out of critical limit at slope stability radar. In: *International Journal of Geo- Engineering*, vol. 8, no. 1, pp. 1–16. DOI: 10.1186/s40703-017-0054-y (2017).
4. Kumar, A., Villuri, V.G.: Role of mining radar in mine slope stability monitoring at open cast mines. In: *Procedia Earth and Planetary Science*, vol. 11, pp. 76–83. DOI: 10.1016/j.proeps.2015.06.010 (2015).
5. Kumar, A., Gorai, A.K.: Geo-spatial Estimation and Forecasting of LULC Vulner- ability Assessment of Mining Activity: A Case Study of Jharia Coal Field, India. In: *Journal of Remote Sensing and GIS*, vol. 7, pp. 253. DOI: 10.4172/2469- 4134.1000253 (2018).
6. Kumar, A., Prasad, S.: Geospatial Evaluation of LULC with Time Series Change in Coal Mining Activity Terrain: A Case Study of Jharia, India. In: *Journal of Mining and Geology*, vol. 55, no. 2, pp. 217–227 (2019).
7. Gustafsson, J.: Colonic barrier function in ulcerative colitis-Interactions between ion and mucus secretion. (2012)
8. Kumar, A., Gorai, A.K.: Application of transfer learning of deep CNN model for classification of time-series satellite images to assess the long-term impacts of coal mining activities on land-use patterns. In: *Geocarto International*, vol. 37, no. 26, pp. 11420–11440. DOI: 10.1080/10106049.2022.2057595 (2022).
9. Kumar, A., Gupta, A., Singh, Y.P., Bhagat, M.: A Deep Neural Network for Classification of Land Use Satellite Datasets in Mining Environments. In: *Journal of Mining and Environment*, vol. 13, no. 3, pp. 797–808. DOI: 10.22044/jme.2022.12262.2224 (2022).
10. Prasad, S., Kumar, A.: Computational Cut-Off Grade Modeling: A Review. In: *International Journal of Earth Science and Geophysics*, vol. 7, no. 2, pp. 048. DOI: 10.35840/2631-5033/1848 (2021).
11. Kumar, A.: Time-domain reflectometry–based real-time slope stability moni- toring in opencast mines: A review. In: *Noise & Vibration Worldwide*, vol. 0957456520924812. DOI: 10.1177/095745652092481 (2020).
12. Petrova, T. V., Nykänen, A., Norrmén, C., Ivanov, K. I., Andersson, L. C., Haglund, C., Puolakkainen, P., Wempe, F., von Melchner, H., Gradwohl, G., et al.: Transcrip- tion factor PROX1 induces colon cancer progression by promoting the transition from benign to highly dysplastic phenotype. In: Cancer Cell, vol. 13, no. 5, pp. 407–419. Elsevier (2008)
13. Pandurangan, A. K., Divya, T., Kumar, K., Dineshbabu, V., Velavan, B., Sud- handiran, G.: Colorectal carcinogenesis: Insights into the cell death and signal transduction pathways: A review. In: World Journal of Gastrointestinal Oncology, vol. 10, no. 9, pp. 244. Baishideng Publishing Group Inc (2018)
14. Raulet, D. H., Guerra, N.: Oncogenic stress sensed by the immune system: role of natural killer cell receptors. In: Nature Reviews Immunology, vol. 9, no. 8, pp. 568–580. Nature Publishing Group UK London (2009)
15. Kumar, A., Gorai, A.K.: A comparative evaluation of deep convolutional neu- ral network and deep neural network-based land use/land cover classifications of mining regions using fused multi-sensor satellite data. In: *Advances in Space Re- search*, vol. 72, no. 11, pp. 4663–4676. DOI: 10.1016/j.asr.2023.08.057 (2023).
16. Kumar, A., Prasad, S.: A Critical Assessment of Sustainable Development in the Indian Coal Mining Sector: A Review. In: *Mining Revue*, vol. 29, no. 2, pp. 1–9. DOI: 10.2478/minrv-2023-0009 (2023).
17. Kumar, A., Gupta, R.: Futuristic study of a criminal facial recognition: An open-source face image dataset. In: *Science Talks*, vol. 6. DOI: 10.1016/j.sctalk.2023.100229 (2023).

18. Kumar, A., Gorai, A.K.: Development of a deep convolutional neural network model for detection and delineation of coal mining regions. In: *Earth Science In- formatics*, vol. 16, no. 2, pp. 1151–1171. DOI: 10.1007/s12145-023-00955-3 (2023).
19. Kumar, A., Gorai, A.K.: Design of an optimized deep learning algorithm for au- tomatic classification of high-resolution satellite dataset (LISS IV) for studying land-use patterns in a mining region. In: *Computers & Geosciences*, vol. 170, pp. 105251. DOI: 10.1016/j.cageo.2022.105251 (2023).
20. Oliveira, S.P., Montezuma, D., Moreira, A., Oliveira, D., Neto, P.C., Monteiro, A., Monteiro, J., Ribeiro, L., Gonçalves, S., Pinto, I.M., et al.: A CAD system for automatic dysplasia grading on H&E cervical whole-slide images. In: *Scientific Reports*, vol. 13, no. 1, pp. 3970. Nature Publishing Group, London (2023).
21. Paygude, P., Ojha, S., Rathi, S., Kumar, A., Bidve, V., Dhumane, A., Devale, P.: A Method to Enhance Privacy Preservation in Cloud Storage through a Three- Layer Scheme for Computational Intelligence in Fog Computing. In: *MethodsX*. Elsevier (Accepted, 2024).
22. Paygude, P., Thite, S., Kumar, A., Bhosle, A., Pawar, R., Mane, R., Gayakwad, M.: A Dataset Revolutionizing Indian Bay Leaf Analysis. In: *Data in Brief*, vol. 2024, pp. 111024. Elsevier (2024).
23. Kumar, A., Prasad, S., Reddy, R.S.: Environmental implications on blasting op- erations in Indian quarry mines. In: *International Journal of Mining and Geo- Engineering*, vol. 58, no. 3, pp. 289–294. Scopus (2024).
24. Kumar, A.: A Promising Automatic System for studying of Coal Mine Sur- faces using Sentinel-2 Data to Assess a Classification on a Pixel-based Pat- tern. In: *Journal of Mining and Environment*, vol. 15, no. 1, pp. 41–54. DOI: 10.22044/jme.2023.13064.2380 (2024).
25. Martirosyan, A., Moreno, E., Gorvel, J.-P.: An evolutionary strategy for a stealthy intracellular Brucella pathogen. In: Immunological Reviews, vol. 240, no. 1, pp. 211–234. Wiley Online Library (2011)
26. Jones, O. T., Calanzani, N., Saji, S., Duffy, S. W., Emery, J., Hamilton, W., Singh, H., de Wit, N. J., Walter, F. M.: Artificial intelligence techniques that may be applied to primary care data to facilitate earlier diagnosis of cancer: systematic review. In: Journal of Medical Internet Research, vol. 23, no. 3, pp. e23483. JMIR Publications, Toronto, Canada (2021)
27. Yip, C.-H., Smith, R. A., Anderson, B. O., Miller, A. B., Thomas, D. B., Ang, E.-S., Caffarella, R. S., Corbex, M., Kreps, G. L., McTiernan, A., et al.: Guideline implementation for breast healthcare in low-and middle-income countries: early detection resource allocation. In: Cancer, vol. 113, no. S8, pp. 2244–2256. Wiley Online Library (2008)
28. Salvi, M., Bosco, M., Molinaro, L., Gambella, A., Papotti, M., Acharya, U. R., Molinari, F.: A hybrid deep learning approach for gland segmentation in prostate histopathological images. In: Artificial Intelligence in Medicine, vol. 115, pp. 102076. Elsevier (2021)
29. Sirinukunwattana, K., Pluim, J. P. W., Chen, H., Qi, X., Heng, P.-A., Guo, Y. B., Wang, L. Y., Matuszewski, B. J., Bruni, E., Sanchez, U., et al.: Gland segmentation in colon histology images: The GLAS challenge contest. In: Medical Image Analysis, vol. 35, pp. 489–502. Elsevier (2017)
30. Wang, L. Y.: Gland Instance Segmentation in Colon Histology Images. Ph.D. the- sis, University of Central Lancashire (2019)
31. Inamdar, M. A., Raghavendra, U., Gudigar, A., Bhandary, S., Salvi, M., Deo, R. C., Barua, P. D., Ciaccio, E. J., Molinari, F., Acharya, U. R.: A Novel Attention-

based model for Semantic Segmentation of Prostate Glands using Histopathological Images. In: IEEE Access. IEEE (2023)
32. Moxley-Wyles, B., Colling, R., Verrill, C.: Artificial intelligence in pathology: An overview. In: Diagnostic Histopathology, vol. 26, no. 11, pp. 513–520. Elsevier (2020)
33. Anwar, S. M., Majid, M., Qayyum, A., Awais, M., Alnowami, M., Khan, M. K.: Medical image analysis using convolutional neural networks: A review. In: Journal of Medical Systems, vol. 42, pp. 1–13. Springer (2018)
34. Kumar, A.: Dynamic COVID-19 Endurance Indicator System for Scientific Deci- sions Using Ensemble Learning Approach with Rapid Data Processing. In: Inter- national Conference on Computation of Artificial Intelligence & Machine Learning, vol. -, no. -, pp. 10–28. Springer Nature Switzerland, Cham (2024)
35. Kumar, A., Singh, J.P., Choudhury, D., Kumar, V., Bisoyi, S.K.: Digital Image Spatial Feature Learning and Mapping Using Geospatial Artificial Intelligence: A Case Study. In: Building Intelligent Systems Using Machine Learning and Deep Learning: Security, Applications and Its Challenges, pp. 205–217. Nova Science Publishers, Inc. (2023). https://doi.org/10.52305/SRTQ8806. ISBN: 979-8-89113-
342-6
36. Kumar, A.: An In-Depth Study of How Blockchain Can Transform the Animal Healthcare Industry: A Review. In: Integration of Artificial Intel- ligence and Machine Learning Methods for Smart Internet of Things Sys- tems and Its Applications, pp. 203–224. Nova Science Publishers, Inc. (2024). https://doi.org/10.52305/MIKT6574
37. Lu, L., Zheng, Y., Carneiro, G., Yang, L.: Deep learning and convolutional neural networks for medical image computing. In: Advances in Computer Vision and Pattern Recognition, vol. 10, pp. 978–3. Springer (2017)
38. Kainz, P., Pfeiffer, M., Urschler, M.: Segmentation and classification of colon glands with deep convolutional neural networks and total variation regularization. In: PeerJ, vol. 5, pp. e3874. PeerJ Inc. (2017)
39. Dabass, M., Dabass, J., Vashisth, S., Vig, R.: A hybrid U-Net model with attention and advanced convolutional learning modules for simultaneous gland segmentation and cancer grade prediction in colorectal histopathological images. In: Intelligence- Based Medicine, vol. 7, pp. 100094. Elsevier (2023)
40. Tharwat, M., Sakr, N. A., El-Sappagh, S., Soliman, H., Kwak, K.-S., Elmogy, M.: Colon cancer diagnosis based on machine learning and deep learning: Modalities and analysis techniques. In: Sensors, vol. 22, no. 23, pp. 9250. MDPI (2022)
41. Masud, M., Sikder, N., Nahid, A.-A., Bairagi, A. K., AlZain, M. A.: A machine learning approach to diagnosing lung and colon cancer using a deep learning-based classification framework. In: Sensors, vol. 21, no. 3, pp. 748. MDPI (2021)
42. Kumar, A., Gill, A.S., Singh, J.P., Ghosh, D.: A Comprehensive and Comparative Examination of Machine Learning Techniques for Diabetes Mellitus Prediction. In: 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 1–5. IEEE (2024, June)
43. Kumar, A., Singh, J.P., Kumar, V., Ghosh, D., Patel, A.K.: A Comprehensive Study of Rainfall Prediction in the Dominant Influence State of Rajasthan (India) Using an Ensemble Linear Regression Approach. In: 2024 1st International Con- ference on Cognitive, Green and Ubiquitous Computing (IC-CGU), pp. 1–6. IEEE (2024, March)
44. Alboaneen, D., Alqarni, R., Alqahtani, S., Alrashidi, M., Alhuda, R., Alyahyan, E., Alshammari, T.: Predicting colorectal cancer using machine and deep learning

algorithms: Challenges and opportunities. In: Big Data and Cognitive Computing, vol. 7, no. 2, pp. 74. MDPI (2023)
45. Hasan, M. I., Ali, M. S., Rahman, M. H., Islam, M. K., et al.: Automated detection and characterization of colon cancer with deep convolutional neural networks. In: Journal of Healthcare Engineering, vol. 2022. Hindawi (2022)
46. Nasir, E. S., Parvaiz, A., Fraz, M. M.: Nuclei and glands instance segmentation in histology images: A narrative review. In: Artificial Intelligence Review, vol. 56, no. 8, pp. 7909–7964. Springer (2023)
47. Dabass, M., Vashisth, S., Vig, R.: Attention-guided deep atrous-residual U-Net architecture for automated gland segmentation in colon histopathology images. In: Informatics in Medicine Unlocked, vol. 27, pp. 100784. Elsevier (2021)
48. Alzubaidi, L., Al-Amidie, M., Al-Asadi, A., Humaidi, A. J., Al-Shamma, O., Fadhel, M. A., Zhang, J., Santamaría, J., Duan, Y.: Novel transfer learning approach for medical imaging with limited labeled data. In: Cancers, vol. 13, no. 7, pp. 1590. MDPI (2021)
49. Kumar, A., Panwar, A.S.: Human Mental State Detection Using Modified Convolutional Neural Network with Leaky Rectified Linear Unit. In: 2024 IEEE Region 10 Symposium (TENSYMP), pp. 1–6. IEEE (2024). https://doi.org/10.1109/TENSYMP61132.2024.10752185
50. Kälviäinen, R.V.J.P.H., Uusitalo, H.: DIARETDB1 Diabetic Retinopathy Database and Evaluation Protocol. In: Medical Image Understanding and Analysis, vol. 2007, p. 61. Citeseer (2007)
51. Tsiknakis, N., Theodoropoulos, D., Manikis, G., Ktistakis, E., Boutsora, O., Berto, A., Marias, K.: Deep Learning for Diabetic Retinopathy Detection and Classifica- tion Based on Fundus Images: A Review. Computers in Biology and Medicine, vol. 135, Article 104599. Elsevier (2021)
52. Zhang, X., Thibault, G., Decencière, E., Marcotegui, B., Laj, B., Danno, R., Erginay, A.: Exudate Detection in Color Retinal Images for Mass Screening of Diabetic Retinopathy. Medical Image Analysis, vol. 18, no. 7, pp. 1026–1043. El- sevier (2014)
53. Castillo Benítez, V.E., Castro Matto, I., Mello Román, J.C., Vázquez Noguera, J.L., García-Torres, M., Ayala, J., Pinto-Roa, D.P., Gardel-Sotomayor, P.E., Facon, J., Grillo, S.A.: Dataset from Fundus Images for the Study of Diabetic Retinopathy. Data Brief, vol. 36, Article 107068. Elsevier (2021). https://doi.org/10.1016/j.dib.2021.107068. PMID: 34307801; PMCID: PMC8257963
54. Panda, N.R., Sahoo, A.K.: A Detailed Systematic Review on Retinal Image Segmentation Methods. Journal of Digital Imaging, vol. 35, no. 5, pp. 1250–1270. Springer (2022). https://doi.org/10.1007/s10278-022-00640-9. PMID: 35508746; PMCID: PMC9582172
55. Li, R., Li, M., Li, J., Zhou, Y.: Connection Sensitive Attention U-Net for Accurate Retinal Vessel Segmentation. arXiv preprint arXiv:1903.05558 (2019)
56. Bhardwaj, C., Jain, S., Sood, M.: Deep Learning-Based Diabetic Retinopa- thy Severity Grading System Employing Quadrant Ensemble Model. Jour- nal of Digital Imaging, vol. 34, no. 2, pp. 440–457. Springer (2021). https://doi.org/10.1007/s10278-021-00418-5. PMID: 33686525; PMCID: PMC8289963
57. Chetoui, M., Akhloufi, M.A.: Explainable End-to-End Deep Learning for Diabetic Retinopathy Detection Across Multiple Datasets. Journal of Medical Imaging, vol. 7, no. 4, Article 044503. SPIE (2020). https://doi.org/10.1117/1.JMI.7.4.044503. PMID: 32904519; PMCID: PMC7456641

58. Rangayyan, R.M., Zhu, X., Ayres, F.J., Ells, A.L.: Detection of the Optic Nerve Head in Fundus Images of the Retina with Gabor Filters and Phase Por- trait Analysis. Journal of Digital Imaging, vol. 23, no. 4, pp. 438–453. Springer (2010). https://doi.org/10.1007/s10278-009-9261-1. PMID: 20066466; PMCID: PMC3046656
59. Fraz, M.M., Remagnino, P., Hoppe, A., Uyyanonvara, B., Rudnicka, A.R., Owen, C.G., Barman, S.A.: An Ensemble Classification-Based Approach Applied to Retinal Blood Vessel Segmentation. IEEE Transactions on Biomedical Engineering, vol. 59, no. 9, pp. 2538–2548. IEEE (2012). https://doi.org/10.1109/TBME.2012.2205687
60. Porwal, P., Pachade, S., Kamble, R., Kokare, M., Deshmukh, G., Sahasrabuddhe, V., Meriaudeau, F.: Indian Diabetic Retinopathy Image Dataset (IDRiD). IEEE Dataport (2018, April 24). https://doi.org/10.21227/H25W98
61. Derwin, D.J., Selvi, S.T., Singh, O.J.: Secondary Observer System for Detection of Microaneurysms in Fundus Images Using Texture Descrip- tors. Journal of Digital Imaging, vol. 33, no. 1, pp. 159–167. Springer (2020). https://doi.org/10.1007/s10278-019-00225-z. PMID: 31144148; PMCID: PMC7064709
62. Papadopoulos, A., Topouzis, F., Delopoulos, A.: An Interpretable Multiple- Instance Approach for the Detection of Referable Diabetic Retinopathy in Fun- dus Images. Scientific Reports, vol. 11, no. 1, Article 14326. Nature Publishing Group (2021). https://doi.org/10.1038/s41598-021-93632-8. PMID: 34253799; PM- CID: PMC8275626