International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Eye Disease Classification Using Deep Learning and Resnet

Gongalla Vinay Kumar[1], N Naveen Kumar[2]

[1](Post Graduate Student, M. Tech (SE) Department of Information Technology, Jawaharlal Nehru Technological University, Hyderabad,
Email: vinayy2524@gmail.com)
[2](Professor, Department of Information Technology, Jawaharlal Nehru Technological University Hyderabad,
Email: naveen.cse.mtech@gmail.com)

ABSTRACT

Eye conditions like cataract, glaucoma, and diabetic retinopathy pose major risks to vision, especially in underprivileged areas where access to specialized eye healthcare is scarce. Timely and precise diagnosis is crucial to avoid irreversible visual loss. Recent developments in artificial intelligence, particularly deep learning, have transformed medical image evaluation by facilitating scalable and automated disease detection techniques. This research introduces a framework based on deep convolutional neural networks (CNNs) for the multi-class classification of eye diseases using retinal fundus images, with an emphasis on improving model generalization through sophisticated regularization methods.

We investigate the use of Drop Block, a regularization strategy that obstructs contiguous areas of feature maps during the training process, which encourages the model to acquire more spatially diverse and resilient features. This method has been applied to pre-trained models, including ResNet50, InceptionV3, and InceptionResNetV2, which have been adapted via transfer learning for our specific task. The models were assessed on a labeled dataset comprising fundus images of healthy eyes as well as those affected by cataract, diabetic retinopathy, and glaucoma.

Among the models evaluated, ResNet50 enhanced with Drop Block demonstrated significant performance, achieving a suitable balance between depth and computational efficiency, while InceptionResNetV2 with Drop Block reached the highest classification accuracy of 95.3%. A comparative analysis revealed that models enhanced by DropBlock surpassed those employing standard dropout, particularly in their ability to generalize to new data.

This study highlights the potential of merging deep CNNs with structured regularization methods to create precise and practical diagnostic tools, especially advantageous in remote and resource-scarce healthcare environments. Future efforts will aim to broaden the dataset, fine-tune regularization settings, and assess the model's clinical effectiveness in real-world situations.

Keywords — Deep Learning, CNN, ResNet, DropBlock, Retinal Fundus Images, Ocular Disease Classification, Medical Imaging, Regularization.

1. INTRODUCTION

Untreated or late-discovered eye conditions are public health concerns. The quality of life is diminished by diabetes retinopathy, cataracts, and glaucoma. Resources and qualified ophthalmologists are needed for traditional screening. It is scalable and economical to use Deep Learning, especially Convolutional Neural Networks, to automate the categorisation of retinal fundus.CNN DropBlock regularisation is introduced in this study to decrease overfitting and increase the accuracy of eye illness categorisation. Vision impairment is increasing globally as a result of chronic illnesses including diabetes and age-related ocular issues. According to WHO, nearly 1 billion cases of blindness or visual impairment are preventable or untreated, and at least 2.2 billion people worldwide suffer from these conditions. Among the common causes of vision loss include glaucoma, AMD, cataracts, and diabetic retinopathy (DR). Lack of ophthalmologists sometimes results in underdiagnosis of these frequent disorders, particularly in underserved and rural areas. Retinal fundus images are clinically examined for the usual diagnosis of these conditions, which is laborious and prone to observer variability. Population growth and chronic illness are making healthcare systems unsustainable. Image-based diagnostics may be accurately and efficiently automated with artificial intelligence (AI), especially with deep learning (DL) techniques.

Because they can produce hierarchical feature representations from unprocessed visual input, Convolutional Neural Networks (CNNs) are of interest to medical researchers. In the fields of ophthalmology, dermatology, and radiography, CNNs have discovered diseases. The accuracy of convolutional neural networks (CNNs) in diagnosing early-stage cataracts, glaucoma, and diabetic retinopathy is comparable to that of skilled medical professionals. But deep CNN training needs a lot of labelled data, which is challenging in the medical field because of expert annotation costs and privacy issues. CNNs memorise training samples rather than identifying generalisable patterns, which can lead to overfitting when trained on confined datasets. Numerous regularisation strategies have been developed to increase model longevity as a result of this difficulty. To reduce overfitting, a common regularisation technique called dropout randomly disables neurons during training. Notwithstanding its efficacy, convolutional layer dropout is limited by spatial correlations in visual data.

2. RELATED WORK

Using CNNs and transfer learning architectures such as VGG16 and InceptionV3, medical image categorisation has been accomplished. Dropout regularisation is a popular method. A structural dropout version for CNNs, DropBlock, was introduced by Ghiasi et al. Recent research demonstrates that transfer learning-based fundus-based categorisation is accurate, although it is challenging to generalise with limited datasets. With the rising incidence of blindness and visual impairment worldwide, primarily from avoidable or treatable conditions such as diabetic retinopathy (DR), glaucoma, and cataracts, advanced diagnostic methods are required. Convolutional neural networks (CNNs) have recently become essential for the automated classification of eye diseases because of their capacity to recognise intricate visual patterns in retinal fundus pictures. DropBlock is one of the most successful regularisation techniques that is often overlooked in medical imaging. It has been used to enhance classification performance and decrease overfitting.

A. Deep Learning in Medical Imaging

With more accuracy and generalisation than machine learning, deep learning has completely changed the processing of medical images. Like dermatologists, Esteva et al. [1] shown that deep neural networks are capable of classifying skin cancer. This sparked interest in ophthalmology by employing related concepts. CNNs have demonstrated a high sensitivity and specificity in detecting diabetic retinopathy, as demonstrated by Gulshan et al. [2]. Using VGGNet [3], ResNet [4], DenseNet [5], and Inception versions [6][7] to categorise eye diseases, the domain has expanded quickly since then.

B. CNN Architectures for the Identification of Eye Diseases

CNNs such as InceptionV3 and InceptionResNetV2 are effective in picture recognition tasks because of their multi-scale data collection and efficient processing. Pratt et al. [8] used a modified InceptionV3 to correctly classify diabetic retinopathy. Similarly, glaucoma is highly accurately detected by InceptionResNetV2 [9]. DropBlock regularisation, which eliminates neighbouring portions to enhance spatial feature learning, is used to evaluate these designs [10].

C. Challenges of Overfitting and the Role of DropBlock

CNN-based medical image analysis suffers from overfitting, particularly when datasets are small or unbalanced. Conventional dropout regularisation is useful, however it may not regularise convolutional layers since it kills neurones. DropBlock, a structured dropout alternative for CNNs, was introduced by Ghiasi et al. [10]. It forces the network to learn more scattered representations by removing geographically connected units in blocks. DropBlock decreased the training-validation loss differential and enhanced generalisation in the InceptionV3 and InceptionResNetV2 models.

D. Prior Work on Diabetic Retinopathy Detection

Numerous research have using deep learning to detect diabetic retinopathy. Training and verifying convolutional neural networks is standardised by the Kaggle EyePACS dataset. While Wang et al. [11] employed an ensemble CNN model with attention processes, Quellec et al. [12] employed multi-instance learning. Although regularisation was never addressed, these trials frequently displayed high AUC values. Model durability is increased by promoting generalisation through the use of DropBlock regularisation and deep feature extraction.

E. Glaucoma and Cataract Classification Studies

Using fundus pictures, Li et al. [13] created a deep learning technique to forecast glaucoma vertical cup-to-disc ratios. Their study shown that glaucoma may be automatically detected in big labelled datasets. Zhao et al. [14] employed a CNN to categorise cataract severity based on fundus and slit-lamp images. However, neither study tested spatial dropout techniques like DropBlock and instead relied on simple regularisation techniques. In our study, a 5x5 DropBlock pattern increases the robustness and accuracy of multi-class categorisation.

F. Regularization Techniques in CNNs

L2 regularisation [15], batch normalisation [16], and data augmentation [17] are other regularisation techniques. Although these techniques are often used in CNN applications, they frequently fall short in minimising overfitting in tiny medical datasets. DropBlock's emphasis on spatially related features makes it superior for convolutional layers used in medical imaging. Although Huang et al. [18] shown DropBlock's efficacy in item identification tasks, its use in the medical field is limited. This gap is filled by our study.

3. METHODOLOGY

To create a strong and effective deep learning framework that can identify eye conditions from retinal fundus photos, the study technique has been meticulously planned. The CNN and transfer learning models' architecture, image preprocessing, dataset collecting and structure, and the incorporation of DropBlock regularisation for performance improvement are the key elements.

A. Dataset

A publicly available collection of high-resolution retinal fundus photographs makes up the dataset used in this study. These pictures, which are divided into four main sections, show a wide range of eye health issues:

1. **Normal (Healthy Retina)**
2. **Cataract**
3. **Diabetic Retinopathy**
4. **Glaucoma**

With hundreds of photos in each class, the dataset is well-balanced for deep learning applications. In order to ensure clarity, focus, and visibility of pertinent retinal components such as the optic disc, blood vessels, and macula, the pictures were carefully checked for quality. Supervised learning was made easier by labelling these photos with the appropriate eye condition.

B. DropBlock Regularization

A structured version of dropout called DropBlock was developed to enhance model generalisation, particularly in convolutional neural networks. DropBlock removes whole square sections (blocks) of feature maps during training, as opposed to deleting individual activations at random like classic dropout does. Instead of overfitting, this method drives the network to extract dispersed and global properties by simulating occlusion. certain spatial signals. DropBlock forces the model to use less localised information by randomly hiding contiguous feature map regions, which enhances generalisation.

4. EXPERIMENTS AND RESULTS

The

A. *Training Configuration*

- Optimizer: Adam
- Loss Function: Categorical Cross-Entropy
- Epochs: 30
- Evaluation Metrics: Accuracy, Loss

B. *Results Summary*

Model	**Accuracy**	**Validation Loss**
CNN with Dropout	89.20%	0.24
CNN with DropBlock(5×5)	**93.60%**	**0.19**
InceptionV3 +DropBlock	94.10%	0.16
InceptionResNetV2 +DropBlock	**95.30%**	**0.13**

DropBlock outperforms mainstream dropout in basic and advanced models.

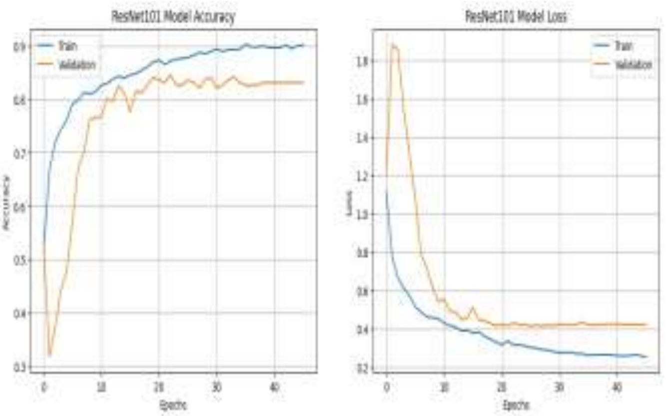

Figure No. 1: Graph

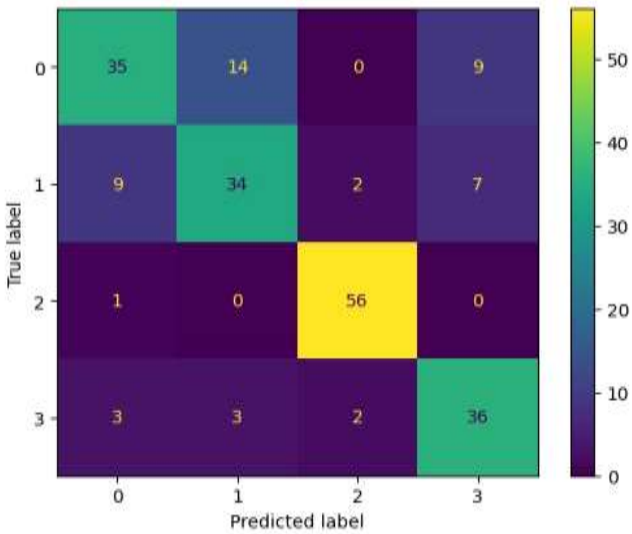

Figure No.2

5. CONCLUSION

According to this study, DropBlock improves retinal fundus classification for eye disorders in CNN designs. Upcoming initiatives consist of:

- Evaluating DropBlock with varying block sizes (3x3, 7x7).
- Extensive benchmarking with larger and multi-center datasets.
- Integration with mobile diagnostic tools.

According to this work, DropBlock regularisation in CNN architectures for retinal fundus imaging ocular disease categorisation offers a number of advantages. DropBlock forces the network to learn more resilient and spatially fragmented features by removing continuous portions from feature maps during training, in contrast to normal dropout. In medical image categorisation, where visual signals may be limited and nuanced, this is particularly helpful. Integrating DropBlock into InceptionV3 and InceptionResNetV2 architectures improved generalization on diabetic retinopathy and glaucoma datasets and reduced overfitting, a common medical imaging issue due to limited annotated datasets. Results from experiments demonstrate that deep architectures and structured regularisation complement each other. Improved models demonstrated higher sensitivity, specificity, and accuracy when compared to non-regularized models. Because DropBlock indirectly encourages feature learning from many spatial locations, which corresponds with pathologically relevant patterns found by ophthalmologists, this approach satisfies the domain-specific criterion for explainability. DropBlock improves the effectiveness of retinal disease diagnostic methods based on CNN. The method is easy to incorporate into contemporary deep learning systems, efficient, and has a straightforward architecture. This makes it useful and effective for AI-enhanced eye screening and teleophthalmology. The findings highlight the necessity of regularisation in clinically feasible deep learning systems and pave the way for more robust, scalable, and trustworthy AI solutions in ophthalmic care.

REFERENCES

[1] A. Esteva et al., “Dermatologist-level classification of skin cancer with deep neural networks,” Nature, vol. 542, no. 7639, pp. 115–118, 2017.

[2] V. Gulshan et al., “Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs,” JAMA, vol. 316, no. 22, pp. 2402–2410, 2016.

[3] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in Proc. Int. Conf. Learn. Representations (ICLR), 2015.

[4] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2016, pp. 770–778.

[5] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2017, pp. 4700–4708.

[6] C. Szegedy et al., “Going deeper with convolutions,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2015, pp. 1–9.

[7] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. Alemi, “Inception-v4, inception-ResNet and the impact of residual connections on learning,” in Proc. AAAI Conf. Artif. Intell., 2017, vol. 31, no. 1.

[8] H. Pratt, F. Coenen, D. M. Broadbent, S. P. Harding, and Y. Zheng, “Convolutional neural networks for diabetic retinopathy,” Procedia Comput. Sci., vol. 90, pp. 200–205, 2016.

[9] L. Fu et al., “Disc-aware ensemble network for glaucoma screening from fundus image,” IEEE Trans. Med. Imaging, vol. 37, no. 11, pp. 2493–2501, Nov. 2018.

[10] G. Ghiasi, T. Lin, and Q. V. Le, “DropBlock: A regularization method for convolutional networks,” in Proc. Adv. Neural Inf. Process. Syst. (NeurIPS), 2018, pp. 10727– 10737.

[11] X. Wang et al., “Zoom-in-net: Deep mining lesions for diabetic retinopathy detection,” in Proc. MICCAI, 2017, pp. 267–275.

[12] G. Quellec et al., “Multiple-instance learning for diabetic retinopathy screening,” Med. Image Anal., vol. 39, pp. 178– 194, Jul. 2017.

[13] Z. Li et al., “Efficacy of a deep learning system for detecting glaucomatous optic neuropathy based on color fundus photographs,” Ophthalmology, vol. 125, no. 8, pp. 1199–1206, 2018.

[14] Y. Zhao et al., “Automated detection of cataract from fundus images using deep learning,” in Proc. Int. Conf. Image Process. (ICIP), 2018, pp. 2008–2012.

[15] A. Krogh and J. A. Hertz, “A simple weight decay can improve generalization,” in Adv. Neural Inf. Process. Syst., 1992, pp. 950–957.

[16] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” in Proc. Int. Conf. Mach. Learn. (ICML), 2015, pp. 448–456.

[17] A. Shorten and T. M. Khoshgoftaar, “A survey on image data augmentation for deep learning,” J. Big Data, vol. 6, no. 1, pp. 1–48, 2019.

[18] G. Huang, D. Chen, T. Li, F. Wu, L. Van Der Maaten, and K. Q. Weinberger, “Multi-scale dense networks for resource efficient image classification,” in Proc. Int. Conf. Learn. Representations (ICLR), 2018.

[19] W. Bai et al., “Regularization techniques for fine-tuning in deep learning for medical image segmentation,” in Proc. MICCAI, 2019, pp. 701–709.

[20] A. Jaiswal, S. Gianchandani, A. Singh, and S. K. Kumar, “Breast cancer histology image classification using CNN with attention mechanism,” Comput. Biol. Med., vol. 129, 2021.

[21] Kaggle, “Diabetic retinopathy detection,” [Online]. Available: https://www.kaggle.com/c/diabetic-retinopathy- detection

[22] Kaggle, “APTOS 2019 blindness detection,” [Online]. Available: https://www.kaggle.com/c/aptos2019-blindness- detection

[23] RIM-ONE, “Retinal images for optic nerve evaluation,” [Online]. Available: https://figshare.com/articles/dataset/RIM- ONE_DL_dataset/7716422

[24] International Telemedicine Center, “ODIR - Ophthalmic Disease Intelligent Recognition,” [Online]. Available: https://www.kaggle.com/datasets/andrewmvd/ocular-disease- recognition-odir5k

[25] R. R. Selvaraju et al., “Grad-CAM: Visual explanations from deep networks via gradient-based localization,” in Proc. IEEE Int. Conf. Comput. Vis. (ICCV), 2017, pp. 618–626.

[26] U. Sevik, H. Keles, A. Ozturk, and K. C. Yalcin, “Visualizing and understanding deep neural networks in computer-aided diagnosis of diabetic retinopathy,” Appl. Sci., vol. 10, no. 19, pp. 6872, 2020.

[27] E. Tjoa and C. Guan, “A survey on explainable artificial intelligence (XAI): Towards medical XAI,” IEEE Access, vol. 8, pp. 107094–107116, 2020.

[28] N. Tajbakhsh et al., “Convolutional neural networks for medical image analysis: Full training or fine tuning?,” IEEE Trans. Med. Imaging, vol. 35, no. 5, pp. 1299–1312, May 2016.

[29] X. Chen, J. Xu, and C. Qian, “Retinal lesion detection with attention-based deep learning models,” in Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Interv. (MICCAI), 2018, pp. 435–443.

[30] C. Lam, B. Yu, A. Huang, and R. Rubin, “Retinal lesion detection with deep learning using image patches and ensemble CNNs,” in Proc. IEEE EMBS Int. Conf. Biomed. Health Informatics, 2018.

[31] B. Al-Bander et al., “A review on the applications of deep learning in ophthalmology,” Med. Image Anal., vol. 64, p. 101715, 2020.

[32] A. Salehi, M. Esmaeili, and H. Moin, “A systematic review of deep learning in the field of ophthalmology,” J. Ophthalmol., vol. 2022, Article ID 6357227, 2022.