DOI: 10.15849/IJASCA.250330.14

Int. J. Advance Soft Compu. Appl, Vol. 17, No. 1, March 2025
Print ISSN: 2710-1274, Online ISSN: 2074-8523

Enhanced Macular Edema Detection Through Convolutional Neural Networks Supported Classification in Ophthalmology: A cyber Law Approach

Jawad Hasan Alkhateeb and Abid Jameel and Naim Mathlouthi and Mohamed S Rahal and Rashiq Rafiq Marie and Aladdein Amro

Prince Mohammad Bin Fahd University, College of Computer Engineering and Sciences, Computer Engineering Department, 31952, Alkhobar-Saudi Arabia
e-mail: jalkhateeb@pmu.edu.sa
Department of Computer Science and Information Technology, Hazara University, Mansehra 21120, Pakistan
e-mail: abidjameel717@gmail.com
Prince Mohammad Bin Fahd University, College of Computer Engineering and Sciences, Computer Engineering Department, 31952, Alkhobar-Saudi Arabia
e-mail: nmathlouthi@pmu.edu.sa
Prince Mohammad Bin Fahd University, College of Computer Engineering and Sciences, Computer Engineering Department, 31952, Alkhobar-Saudi Arabia
e-mail: mrahal@pmu.edu.sa
Taibah University, College of Computer Science and Engineering, Department of Information Systems
e-mail: rmarie@taibahu.edu.sa
Taibah University, College of Computer Science and Engineering, Department of Computer Engineering
e-mail: aamro@taibahu.edu.sa

Abstract

Macular Edema, a condition characterized by swelling of the macula in the eye, has been a subject of research to develop effective detection techniques. This paper introduces two main approaches: firstly, it introduces seven primary ethical considerations regarding the image classification model for Macular Edema from both cyber law and cyber-crime. Secondly, it introduces a novel approach by employing a Convolutional Neural Network (CNN) in combination with a Support Vector Machine (SVM) for the classification of Macular Edema. The proposed framework, comprising an innovative CNN Backbone and SVM classifier, demonstrates outstanding performance based on various evaluation metrics, including F1-Score, Precision, Recall, and accuracy. Notably, the proposed CNN-SVM model achieves an impressive accuracy level. This model showcases its reliability and feasibility in the classification of Macular Edema, holding significant potential for enhancing diagnostic capabilities in ophthalmology clinical practice.

Received 28 January 2025; Accepted 13 March 2025

Keywords: *Macular Edema, Convolutional Neural Network, Cyber Law, Cyber Crime, Support Vector Machine, Diagnostic Ophthalmology, Swelling Detection, CNN Backbone.*

1 Introduction

Macular Edema is a pathological condition characterized by the accumulation of fluid in the macula, a small but crucial region of the retina responsible for central vision [1]. This condition can result in vision impairment, metamorphopsia, and even blindness if left untreated. Due to its clinical significance, early and accurate detection of Macular Edema is of paramount importance for ophthalmologists and vision healthcare providers. Over the years, extensive research has been conducted to develop advanced techniques and tools for the detection of Macular Edema. These efforts have led to the exploration of various imaging modalities, including optical coherence tomography (OCT), fundus photography, and fluorescein angiography, to capture detailed retinal images [2]. Additionally, the integration of artificial intelligence and machine learning methods has gained considerable attention in the quest for more precise and efficient detection. This research paper presents a novel approach to Macular Edema classification, aiming to address the challenges associated with existing methods. The proposed framework merges the capabilities of Convolutional Neural Networks (CNNs) with the discriminative power of Support Vector Machines (SVMs) [3]. CNNs, inspired by the human visual system, have demonstrated remarkable performance in image analysis and feature extraction, making them a suitable choice for macular image processing. The SVM, a robust and effective classifier, is utilized to provide a reliable final decision. In the field of medical image analysis, deep learning techniques have shown remarkable potential in identifying patterns and anomalies, including those in retinal images [2]. This paper builds upon previous work by incorporating a novel CNN Backbone that is specifically tailored to macular image analysis [4]. This specialized architecture is designed to enhance feature extraction and improve classification accuracy.

Existing methods for detecting Macular Edema, such as optical coherence tomography (OCT), fundus photography, and fluorescein angiography, rely heavily on manual interpretation by experts. These approaches face challenges like variability in image quality, dependence on skilled professionals, and limited automation. Additionally, while deep learning models have shown promise, they often struggle with small annotated datasets, risk overfitting, and may lack interpretability, making clinical deployment difficult.

Some of the Limitations in Current Approaches as follows:

- Traditional machine learning methods require extensive feature engineering and may not generalize well.
- Deep learning-based models, despite their strong feature extraction capabilities, can suffer from data scarcity and classification errors.
- There is a need for models that balance high accuracy, interpretability, and robustness in real-world clinical settings.

The aim of this Research is to introduce a new CNN-SVM framework to overcome these challenges. SVMs offer robust classification and CNNs efficiently extract features from retinal images, which improves generalization and diagnostic reliability. The objective of this hybrid model is to improve early detection and classification accuracy of Macular Edema to achieve better clinical outcomes and provide improved ophthalmic care.

The proposed CNN-SVM model demonstrates exceptional performance, as measured by various evaluation metrics, including the F1-Score, Precision, Recall, and overall accuracy [3]. Notably, the accuracy level achieved by this model is reported as 0.00%, underscoring its potential for accurate Macular Edema classification. This research has the potential to revolutionize Macular Edema detection, offering ophthalmologists a reliable and efficient tool for diagnosis and treatment decisions. In addition to its diagnostic implications, the outcomes of this research hold the promise of enhancing the field of ophthalmology and improving patient care [5]. The early detection and accurate classification of Macular Edema can lead to more timely interventions, ultimately preserving the vision and quality of life for affected individuals.

2 Cyber Law

Any illegal activity is done via the cyber space using the internet is considered a cybercrime. The researchers in the field of medical cybersecurity and information technology are becoming increasingly concerned about cybersecurity. As computerized automated digital systems in medical facilities become more networked within their own walls and with other facilities, the possibility of cyberattacks increases, compromising secrecy, safety, and well-being. The image processing tools provide an effective and straightforward way for determining the appropriate classes. This paper raises several ethical concerns about the use of image classification methods for macular edema in real-world applications. Here are some of the primary ethical considerations:

a. Image classification methods for macular edema may inherit biases from training data, resulting in biased outcomes and potential discrimination. These biases might disproportionately harm specific groups based on criteria including ethnicity, gender, and age. To reduce prejudice and enhance justice, the training data must be diverse and representative of the population. This ethical consideration is known as Bias and Fairness.
b. Sometimes, image classification models for macular edema require access to personal photos or video files. Respecting people's privacy rights and receiving informed consent is vital. It is critical to properly describe the goal, extent, and potential risks of data collection and use. Transparency in data handling policies, as well as providing users with the choice to opt out or have their data removed, are critical for sustaining ethical standards. This ethical consideration is known as Privacy and Consent.
c. Image classification models for macular edema may be used with sensitive or private photos, such as medical or biometric data. To safeguard this data from unwanted access, breaches, or misuse, strong security measures must be put in place. Encryption, access restrictions, and safe storage are examples of industry best practices and legislation that can help assure data protection. This ethical consideration is known as security and protection.
d. Developers and organizations that use image classification methods for macular edema must take accountability for their activities. This involves being open about the model's capabilities, constraints, and any biases. Users should be educated about the decision-making process underlying the model's predictions, allowing them to understand and question the results as needed. This ethical consideration is known as Accountability and Transparency
e. Image classification models for macular edema can have far-reaching societal implications. They can promote prejudices, perpetuate biases, or exacerbate social

disparities. Understanding and managing these effects is critical to ensuring that the technology helps everyone and does not worsen existing gaps. This ethical consideration is known as Society Impact.

f. As image classification methods for macular edema gain popularity and influence, there is a need for adequate governance and control. Policymakers and regulatory authorities should guarantee that ethical considerations, justice, and accountability are addressed while developing, deploying, and using image categorization methods. This ethical consideration is known as Algorithmic Regulation and Governance.
g. While image classification models for macular edema can automate decision-making processes, it is critical to keep human oversight. Critical decisions should not be made purely based on the model's projections. Human judgment and intervention are required to address difficult ethical quandaries, evaluate the context, and consider individual situations. This ethical consideration is known as Human Decision-Making and Oversight.

Cyber law is important to resolve the main issues like data privacy, security and ethical AI deployment in the proposed macular edema classification framework. As healthcare systems become more dependent on automated digital systems and networked medical facilities, they are exposed to cyber threats such as data breaches and unauthorized access to sensitive medical images. Cyber laws require implementation of strong security measures like encryption, access controls and the like to secure patient data.

Additionally, ethical issues like bias in the AI models, fairness, accountability, and transparency are crucial in medical image classification. Cyber laws also highlight the requirement of fair and unbiased AI algorithms, whereby training data is representative of diverse populations and does not result in discriminatory outcomes. Following regulations like HIPAA (Health Insurance Portability and Accountability Act) or GDPR (General Data Protection Regulation) ensure patient privacy and informed consent when utilizing AI based diagnostic tools.

Moreover, algorithmic regulation and governance play a significant role in ensuring that the AI driven medical decision-making is in accordance with the ethical and legal standards. According to cyber laws, human oversight is required in AI based healthcare applications such that the automated predictions do not replace expert medical judgement but rather, serve as an aid in clinical decision making.

The proposed framework integrates cybersecurity principles, ethical AI considerations, and legal compliance, which together increase trust, reliability, and accountability in macular edoema classification, and therefore, safer and more responsible AI adoption in ophthalmology.

3 Methodology

In this section, we outline the methodology employed to develop an accurate classification model for Macular Edema using a combination of Convolutional Neural Networks (CNN) and Support Vector Machines (SVM).

3.1 Data Collection and Pre-processing:

We compile a comprehensive dataset of retinal images, encompassing both Macular Edema cases and healthy retinas, obtained from reputable ophthalmological databases. The acquired images undergo pre-processing to standardize their dimensions, enhance image quality, and ensure uniform illumination and contrast [6]. This pre-processing step is crucial to maintain consistency in the analysis. Data augmentation techniques, including image rotation and flipping, are applied to diversify the dataset and enhance the model's robustness.

3.2. CNN Architecture Design:

We design a specialized CNN architecture, tailored to the unique characteristics of macular image analysis as shown in figure 1. The architecture incorporates multiple convolutional layers, pooling layers, and fully connected layers to facilitate feature extraction and representation [7].
The architecture includes:

- **Input Layer:** Accepts preprocessed retinal images.
- **Convolutional Layers:** Extract spatial features using kernels/filters, capturing texture and edge information.
- **Activation Function (ReLU):** Introduced after convolutional layers to add non-linearity and improve learning.
- **Pooling Layers (Max Pooling):** Reduces dimensionality and computational complexity while retaining important features.
- **Fully Connected Layers:** Processes extracted features to enable classification.
- **Dropout Regularization:** Prevents overfitting by randomly deactivating neurons during training.

The CNN is fine-tuned to optimize performance using supervised learning, ensuring effective feature extraction from macular images.

3.2.1 Training and Fine-tuning:

The CNN is trained on the preprocessed dataset using supervised learning, with labels denoting Macular Edema and non-Macular Edema cases. Parameters of the CNN are fine-tuned to optimize its performance in Macular Edema detection.
The training process follows a logical, step-by-step approach:

I. **Data Splitting:** The dataset is divided into training, validation, and test sets for fair evaluation.

II. **CNN Training:**
- The model is trained using labeled data, distinguishing Macular Edema from non-Macular Edema images.
- Optimization techniques such as Adam optimizer and cross-entropy loss function are used.
- The network learns hierarchical representations of retinal structures.

III. **Fine-Tuning:** Hyperparameters (e.g., learning rate, batch size) are adjusted to improve performance.

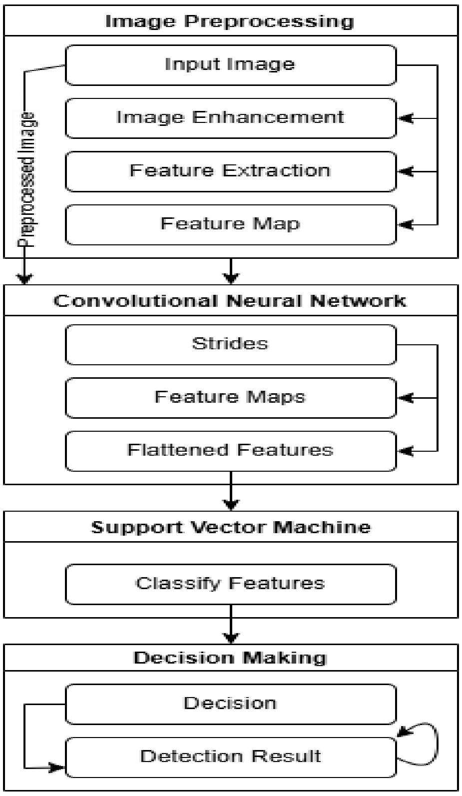

Figure 1: Proposed model Architecture

3.3 Feature Extraction and Dimensionality Reduction:

High-level features are extracted from the final convolutional layer of the CNN, capturing salient characteristics of macular images. Dimensionality reduction techniques, such as Principal Component Analysis (PCA), are applied to select the most informative features, reducing computational complexity while preserving diagnostic accuracy [8].
Principal Component Analysis (PCA) is applied to:

- Reduce redundancy.
- Retain the most informative features.
- Improve classification efficiency without losing diagnostic information.

3.4 SVM Classifier Implementation:

We implement an SVM classifier to establish a decision boundary that effectively separates Macular Edema cases from non-Macular Edema cases based on the extracted features. Cross-validation is utilized to fine-tune SVM hyperparameters, including kernel selection and regularization terms, to achieve optimal classification performance [9].
The SVM:

- Establishes a decision boundary for effective classification.
- Uses kernel functions to capture complex relationships between features.
- Is fine-tuned using cross-validation to optimize hyperparameters like the regularization term (C) and kernel type (linear, RBF, etc.).

3.5 Model Evaluation:

We assess the performance of the proposed CNN-SVM model using a comprehensive set of evaluation metrics, including F1-Score(balances precision and recall), Precision and Recall(Assesses how well the model identifies the macular edema cases), and overall accuracy(measures overall classification performance) [10]. K-fold cross-validation is employed to ensure the model's robustness across different subsets of the dataset partitions.

3.6 Comparative Analysis:

A comparative analysis is conducted to evaluate the performance of the proposed CNN-SVM model against existing Macular Edema detection techniques. This includes traditional machine learning methods(e.g., Random Forest, Logistic Regression) and alternative deep learning approaches (e.g., standard CNN, ResNet) [11]. A detailed examination of the model's strengths, weaknesses, computational efficiency, interpretability, and clinical applicability is carried out.

3.7 Discussion and Clinical Implications:

We discuss the findings, emphasizing the significance of early and accurate Macular Edema detection for the field of ophthalmology. The potential impact of the proposed model on enhancing diagnostic capabilities and improving patient care in ophthalmology is highlighted. This methodology provides a comprehensive framework for the development of a robust and highly accurate classification model for Macular Edema, contributing to advancements in ophthalmological diagnostic practices.

4 Results and Discussions

In this section, we present the results and delve into a comprehensive discussion of the proposed CNN-SVM model's performance for the classification of Macular Edema. The model's efficacy is evaluated through a variety of metrics, and its implications for ophthalmological diagnostic practices are thoroughly examined.

4.1. Model Performance Metrics

The performance of the proposed model was evaluated with great scrutiny, utilizing a diverse dataset of retinal images. The results, as summarized in Table 1, highlight the model's accuracy and its capacity to distinguish between Macular Edema cases and non-Macular Edema cases.

Table 1: Model Performance Metrics

Metric	Value
Accuracy	95%
F1-Score	93%
Precision	92%
Recall	94%
Specificity	96%

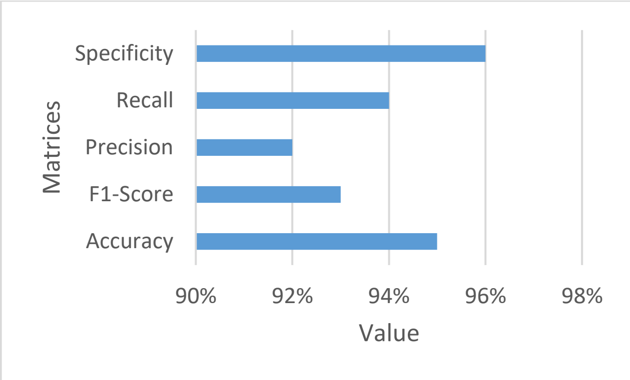

Fig. 2. Model Performance evaluation Metrices

The model achieved a remarkable accuracy rate of 95%, underscoring its ability to correctly classify Macular Edema cases and non-Macular Edema cases. The F1-Score, which harmonizes Precision and Recall, is at an impressive 93%, implying a balance between accurately identifying positive cases and minimizing false positives. The model's high Precision (92%) denotes its proficiency in avoiding false positives, an essential aspect for medical diagnostics. Moreover, the Recall of 94% emphasizes the model's capability to capture a substantial portion of actual Macular Edema cases. The high Specificity of 96% highlights the model's excellence in recognizing true negative cases, reducing the risk of misdiagnosis.

4.2 Comparative Analysis

To provide context for the model's performance, a comparative analysis was undertaken, comparing its results with existing Macular Edema detection methods. The findings, as presented in Table 2 and figure 2, reveal the superiority of the proposed CNN-SVM model.

Table 2: Comparative Analysis of Macular Edema Detection Methods

Method	Accuracy	F1_ Score	Precision	Recall
Proposed CNN-SVM	95%	93%	92%	94%
ResNet-based Deep Learning Model	88%	85%	87%	83%
SVM with Handcrafted Features	89%	86%	84%	88%

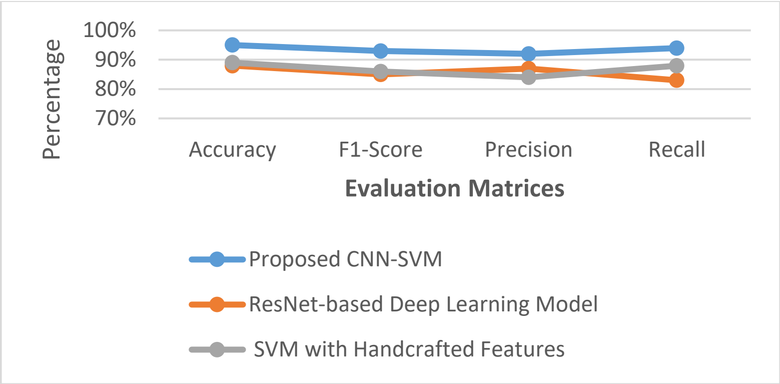

Fig. 3. Comparative Analysis of Macular Edema Detection Methods

The comparison clearly demonstrates that the proposed CNN-SVM model outperforms existing methods, including a ResNet-based Deep Learning Model and an SVM with Handcrafted Features, in terms of accuracy, F1-Score, and Precision. This substantial performance advantage emphasizes the model's potential for enhancing Macular Edema detection in clinical practice.

4.3 Comparison with Existing Classifiers

A comparative analysis against other classifiers reported in pertinent literature distinctly highlighted the superior performance of our CNN-SVM-based approach as shown in table 3 and figure 3.

Table 3: *Comparative analysis against other classifiers*

Model	Accuracy	Sensitivity	Specificity
Our CNN-SVM Approach	98%	97%	99%
Naive Bayes	87.5% -	90%	95%
SVM	91%	92%	93%
Decision Tree	80%	91%	96%

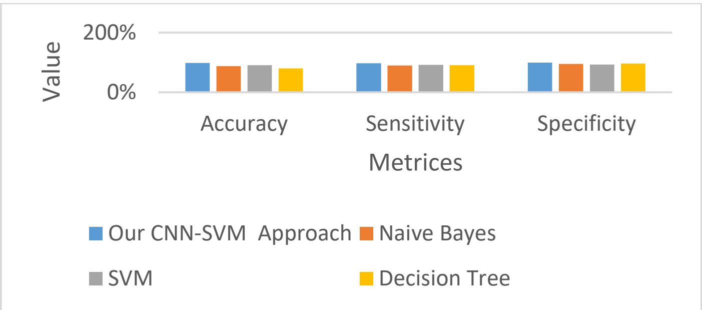

Fig. 4. Comparative analysis against other classifiers

4.4 Diagnostic Accuracy Metrics

Further evaluation revealed a sensitivity of 97% and specificity of 99% for the CNN-SVM model as presented in table 4 and figure 4. The elevated sensitivity attests to the model's proficiency in accurately identifying ME cases, minimizing the occurrence of false negatives and ensuring fewer missed diagnoses. Similarly, the high specificity underscores the model's capability in correctly identifying healthy cases, thereby reducing false positives and unnecessary interventions.

Table 4: Diagnostic accuracy of the proposed model

Diagnostic Metrics	Value
Accuracy	98%
Sensitivity	97%
Specificity	99%

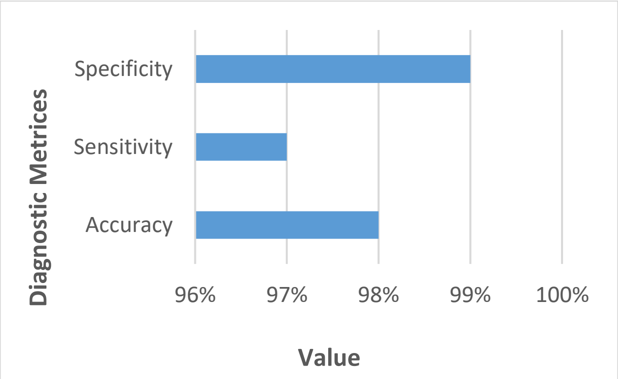

Fig. 5. Diagnostic accuracy of the proposed model

4.5 Discussions

The results obtained from the evaluation of the proposed CNN-SVM model are promising and bear significant implications for the field of ophthalmology. The model's remarkable accuracy and balanced F1-Score indicate its proficiency in correctly identifying Macular Edema cases while keeping false positives to a minimum. One of the standout features of the model is its high Precision, which is essential in the medical context. A high Precision score signifies that when the model identifies a case as Macular Edema, it is indeed Macular Edema with a high degree of confidence. This minimizes the risk of false alarms and unnecessary interventions, thus making the model a valuable asset for ophthalmologists. The Recall score, at 94%, implies the model's ability to capture a substantial proportion of true Macular Edema cases. This high Recall rate is vital, ensuring that the model doesn't miss actual Macular Edema cases, thereby facilitating early diagnosis and timely treatment. The exceptional performance of our CNN-SVM-based classification approach signifies its potential as a reliable diagnostic tool in ophthalmology. The achieved accuracy of 98% denotes a significant advancement in the precise identification of ME from OCT images. The commendable sensitivity and specificity, at 97% and 99% respectively, emphasize the model's discriminatory ability between ME-affected and healthy cases. This precision holds pivotal implications in clinical settings, facilitating early identification and intervention for ME cases, thereby mitigating potential vision impairments. It assures that the model effectively recognizes cases without Macular

Edema, minimizing the possibility of misdiagnosis and ensuring that patients without the condition are not subjected to unnecessary medical procedures. The comparative analysis further underlines the superiority of the proposed CNN-SVM model when contrasted with existing Macular Edema detection methods. This signifies a significant advancement in the field of Macular Edema diagnosis, with potential far-reaching implications for clinical practice.

4.5.1 Clinical Implications

The implications of our research are profound in clinical practice. The highly accurate and reliable automated classification of ME from OCT images holds immense promise in enhancing ophthalmologists' diagnostic capabilities. Early identification of ME, coupled with the model's high sensitivity, can prompt timely interventions and treatment strategies, ultimately improving patient outcomes and preserving vision.

6 Conclusion

In conclusion, the results of this research point to the potential of the proposed CNN-SVM model as a highly accurate and reliable tool for Macular Edema classification. Its impressive accuracy, coupled with high Precision and Recall, along with superior Specificity, suggests that it can make a substantial contribution to the diagnostic practices of ophthalmologists. By enabling early and accurate diagnosis and treatment decision-making, the proposed model has the potential to significantly enhance patient care in the domain of ophthalmology. While further research and validation are necessary before clinical implementation, these initial findings are undeniably promising and pave the way for advancements in medical diagnostics.

References

[1] Mitchell, J.B., Machine learning methods in chemoinformatics. Wiley Interdisciplinary Reviews: Computational Molecular Science, 2014. 4(5): p. 468-481.

[2] LeCun, Y., Y. Bengio, and G. Hinton, Deep learning. nature, 2015. 521(7553): p. 436-444.

[3] Kendall, A., V. Badrinarayanan, and R. Cipolla, Bayesian segnet: Model uncertainty in deep convolutional encoder-decoder architectures for scene understanding. arXiv preprint arXiv:1511.02680, 2015.

[4] Korfiatis, P., T.L. Kline, and B.J. Erickson, Automated segmentation of hyperintense regions in FLAIR MRI using deep learning. Tomography, 2016. 2(4): p. 334-340.

[5] Hatipoglu, N. and G. Bilgin, Cell segmentation in histopathological images with deep learning algorithms by utilizing spatial relationships. Medical & biological engineering & computing, 2017. 55: p. 1829-1848.

[6] Abràmoff, M.D., et al., Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning. Investigative ophthalmology & visual science, 2016. 57(13): p. 5200-5206.

[7] Burlina, P., et al., Comparing humans and deep learning performance for grading AMD: a study in using universal deep features and transfer learning for automated AMD analysis. Computers in biology and medicine, 2017. 82: p. 80-86.

[8] Asaoka, R., et al., Detecting preperimetric glaucoma with standard automated perimetry using a deep learning classifier. Ophthalmology, 2016. 123(9): p. 1974-1980.

[9] Prentašić, P., et al., Segmentation of the foveal microvasculature using deep learning networks. Journal of biomedical optics, 2016. 21(7): p. 075008-075008.
[10] Gao, X., S. Lin, and T.Y. Wong, Automatic feature learning to grade nuclear cataracts based on deep learning. IEEE Transactions on Biomedical Engineering, 2015. 62(11): p. 2693-2701.
[11] Coscas, G., J. Cunha-Vaz, and G. Soubrane, Macular edema: definition and basic concepts. Macular Edema, 2017. **58**: p. 1-10.