A

SYNOPSIS REPORT

On

"DETECTION OF DIABETIC RETINOPATHY USING MACHINE LEARNING"

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ABSTRACT

Diabetic retinopathy (DR) is a severe complication of diabetes that can result in vision loss and blindness if not diagnosed and treated early. Early diagnosis is essential for preventing complications, but manual examination of retinal images is time-consuming and susceptible to human error. This research aims to develop a machine learning-based system for the automatic detection and classification of diabetic retinopathy using retinal fundus images. We explore several state-of-the-art Convolutional Neural Networks (CNN) architectures, including VGG16, VGG19, ResNet50, ResNet152V2, MobileNetV2, and EfficientNetB7, to analyse retinal images and classify them based on the presence and severity of DR.

Among these models, MobileNetV2 was selected for the final system due to its lightweight structure and high performance. This system can assist healthcare professionals by automating DR detection, leading to faster and more accurate diagnoses. Our model achieved 98% accuracy in both binary and multiclass classifications, demonstrating its robustness and potential for deployment in real-world clinical environments, particularly in resource-constrained settings. The system aims to improve patient outcomes by facilitating earlier detection and timely intervention, thereby reducing the risk of vision loss and blindness.

INTRODUCTION

Diabetic retinopathy is a serious eye condition caused by high blood sugar levels in diabetic patients. Over time, elevated blood sugar levels can damage the blood vessels in the retina, leading to vision impairment and blindness if left untreated. As the prevalence of diabetes continues to rise globally, the importance of early DR detection has grown significantly. Traditionally, ophthalmologists manually examine retinal images to detect signs of DR, but this process is time-consuming, labor-intensive, and prone to errors. Advances in technology, particularly machine learning, have opened opportunities for automating this process and improving accuracy.

Machine learning, specifically deep learning techniques such as Convolutional Neural Networks (CNNs), has revolutionized image analysis, making it possible to automatically detect abnormalities in medical images, including those of the retina. This project aims to develop an automated system using various CNN architectures to detect diabetic retinopathy from retinal fundus images. While multiple CNN models like VGG16, VGG19, ResNet50, ResNet152V2, and EfficientNetB7 were considered, MobileNetV2 was selected as the final model due to its balance between accuracy and computational efficiency.

This project is significant because it addresses the need for faster, more accurate, and scalable DR detection. The proposed system is designed to assist healthcare professionals in diagnosing diabetic retinopathy early, leading to timely treatment and a reduction in the risk of blindness. Furthermore, this automated solution can be deployed in remote or underserved regions, providing access to critical eye care without the need for specialist intervention at every location.

AIMS & OBJECTIVES OF PROJECT

AIM:

The aim of this project is to develop a scalable and accurate automated system for the early detection and classification of diabetic retinopathy using advanced machine learning techniques. By leveraging Convolutional Neural Networks (CNNs), including MobileNetV2, the system will analyze retinal images to assist healthcare professionals in diagnosing diabetic retinopathy, improving early detection, and enabling timely interventions to prevent vision loss.

OBJECTIVES:

1. **Automate Diabetic Retinopathy Detection**

   Develop a deep learning-based system using CNNs to automatically detect and classify diabetic retinopathy from retinal images with high accuracy.

2. **Dataset Collection and Preprocessing**

   Collect retinal image datasets, ensuring comprehensive representation of various stages of diabetic retinopathy, and preprocess the images to ensure consistency and quality for analysis.

3. **Model Implementation**

   Apply and evaluate multiple machine learning models (VGG16, VGG19, ResNet50, ResNet152V2, MobileNetV2, and EfficientNetB7) to optimize detection performance and finalize MobileNetV2 for the model due to its computational efficiency and accuracy.

4. **Performance Evaluation**

   Assess model performance using metrics like accuracy, precision, recall, and F1-score for both binary (DR vs. no DR) and multiclass classification to ensure robust and reliable detection across different stages of the disease.

5. **User-Friendly Interface Development**

   Create a simple and intuitive interface for healthcare professionals to upload retinal images and receive automated diagnostic results, assisting in decision-making for further treatment.

6. **Scalability and Deployment**
   Ensure the system is scalable and deployable in clinical settings, mobile health units, or telemedicine platforms, enabling widespread usage, especially in regions with limited access to specialists.

7. **Enhance Early Detection and Treatment Outcomes**
   Contribute to earlier diagnoses, timely interventions, and improved disease management, thereby reducing the risk of vision loss and improving patient outcomes globally.

LITERATURE REVIEW

Diabetic Retinopathy (DR) is a significant complication of diabetes, characterized by damage to the blood vessels in the retina, leading to vision impairment and potentially blindness if not treated early. According to the International Diabetes Federation, the global prevalence of diabetes is increasing, heightening the urgency for early detection of DR to prevent vision loss. Traditional diagnosis of DR requires manual evaluation of retinal images by ophthalmologists, a process that is time-consuming, labor-intensive, and dependent on specialized skills. With the advancements in artificial intelligence (AI) and deep learning, automated systems are now emerging as a reliable alternative for diagnosing diabetic retinopathy.

Machine Learning in Medical Image Analysis

Machine learning, particularly deep learning, has revolutionized medical image analysis, enabling more efficient and accurate diagnostic tools. The use of Convolutional Neural Networks (CNNs), which excel in image classification tasks, has become a primary approach in detecting diabetic retinopathy. CNNs automatically learn important spatial features from medical images, eliminating the need for manual feature extraction.

Convolutional Neural Networks (CNNs)

CNNs have been widely adopted for diabetic retinopathy detection due to their ability to capture intricate details from images. Various layers in CNNs, such as convolutional, pooling, and fully connected layers, work together to extract features that indicate abnormalities in retinal images, such as microaneurysms, hemorrhages, and exudates, which are early indicators of DR. CNN-based models have been shown to outperform traditional machine learning methods in medical image analysis, providing faster and more accurate results.

VGG16 and VGG19

VGG16 and VGG19, developed by the Visual Geometry Group at the University of Oxford, have become benchmarks in image classification tasks. These architectures consist of 16 and 19 layers, respectively, and are known for their simplicity and depth, which allow them to capture detailed features from images. In diabetic retinopathy detection, both VGG16 and VGG19 have been utilized to classify retinal images by extracting hierarchical features that indicate the presence of DR.

ResNet50 and ResNet152V2

ResNet (Residual Networks), introduced by He et al. (2015), solved the problem of vanishing gradients in deep networks by introducing residual learning. ResNet50, a 50-layer deep network, and ResNet152V2, a more advanced version with 152 layers, use shortcut connections to skip layers, allowing the model to retain feature information over very deep architectures. These models have been particularly effective in medical image analysis, including DR detection, where they capture both shallow and deep features for more accurate classification.

MobileNetV2

MobileNetV2, designed by Google, is a lightweight and efficient deep learning model optimized for mobile and low-resource environments. It uses depthwise separable convolutions to significantly reduce the number of parameters while maintaining high classification accuracy. MobileNetV2 has been widely applied in resource-constrained medical applications, making it a strong candidate for real-time diabetic retinopathy detection. Due to its balance of performance and computational efficiency, MobileNetV2 is the final model selected for this project.

EfficientNetB7

EfficientNet, introduced by Tan and Le (2019), is an optimized deep learning model that scales the network's depth, width, and resolution systematically. EfficientNetB7, one of the largest models in the EfficientNet family, has achieved state-of-the-art results in image classification tasks while using fewer parameters than traditional models like ResNet. Its ability to balance accuracy and computational efficiency makes it an excellent choice for large-scale detection tasks like diabetic retinopathy.

Transfer Learning and Data Augmentation

Transfer learning has played a crucial role in medical image analysis, where the availability of large annotated datasets is often limited. By leveraging pre-trained models, such as those trained on ImageNet, transfer learning allows for faster training and higher accuracy when applied to smaller, domain-specific datasets like retinal images.

Data augmentation, another critical technique, helps enhance model performance by artificially increasing the size and diversity of the training dataset. Transformations such as rotation, flipping, and zooming introduce variability in the dataset, enabling the model to generalize better to unseen images and reducing the risk of overfitting.

PROPOSED WORK

The proposed work aims to develop an automated system for early detection and classification of Diabetic Retinopathy (DR) using deep learning techniques. The system will analyze retinal images and classify them based on the severity of DR, thereby assisting healthcare professionals in diagnosing the disease quickly and accurately. The core of the system will be based on Convolutional Neural Networks (CNNs) and other advanced architectures, including VGG16, VGG19, ResNet50, ResNet152V2, MobileNetV2, and EfficientNetB7. The final model will utilize MobileNetV2 due to its efficiency, high accuracy, and suitability for resource-constrained environments.

1. Dataset Collection and Preprocessing

Dataset Collection:
The system will use publicly available datasets, such as:

- **APTOS 2019 Blindness Detection** dataset from Kaggle
- **Diabetic Retinopathy Detection** dataset from Kaggle

These datasets consist of retinal fundus images labeled according to the severity of DR, ranging from no DR to proliferative DR. The images will be split into training, validation, and testing sets to ensure effective training and model evaluation.

Preprocessing:
To ensure the quality and uniformity of images, the following preprocessing steps will be applied:

- **Resizing:** All images will be resized to a standard size (e.g., 224x224 pixels) to ensure consistency across the dataset.
- **Normalization:** Pixel values will be normalized to a range of 0 to 1 to facilitate smoother convergence during training.
- **Data Augmentation:** Techniques such as rotation, flipping, scaling, and brightness adjustments will be used to artificially increase the dataset's size and variability. This helps prevent overfitting and improves the model’s generalization to unseen data.

2. Feature Extraction and Model Selection

Feature Extraction Using CNNs:

CNNs will be employed for automated feature extraction from retinal images. These features will include microaneurysms, hemorrhages, and other abnormalities indicative of DR. No manual feature extraction will be necessary, as the CNNs will learn these patterns during the training process.

Model Architectures:
Several deep learning architectures will be implemented to compare performance:

- **VGG16 and VGG19:** These networks, with 16 and 19 layers respectively, will be used to extract high-level features from the retinal images.

- **ResNet50 and ResNet152V2:** Residual networks will be used to overcome the vanishing gradient problem and capture complex patterns in the images.
- **MobileNetV2:** This lightweight model will be used for real-time, resource-efficient DR detection. It is highly suited for mobile and low-computation environments, which is why it will be the final model.
- **EfficientNetB7:** This architecture will be applied to maximize accuracy while keeping the model computationally efficient.

3. Model Training and Transfer Learning

Training Process:

The dataset will be split into training, validation, and test sets. During the training process, the deep learning models will learn to classify retinal images based on the severity of diabetic retinopathy. The training process will utilize transfer learning, where pre-trained models like ResNet and EfficientNet, which have been trained on large-scale datasets (e.g., ImageNet), will be fine-tuned on the retinal image dataset to improve performance.

Transfer Learning:

Since annotated medical datasets are often limited, transfer learning will help expedite training and improve model accuracy. Pre-trained models will leverage existing knowledge gained from large datasets and apply it to diabetic retinopathy detection. Fine-tuning will involve adjusting the final layers of the pre-trained models to adapt them to the specific characteristics of retinal images.

Data Augmentation:

Augmentation techniques, such as image rotation, zoom, and horizontal flipping, will be applied during the training process to improve model generalization and reduce overfitting.

4. Model Evaluation and Performance Metrics

Evaluation Metrics:
The models will be evaluated using the following metrics to assess their performance:

- **Accuracy:** The overall percentage of correctly classified images.
- **Precision:** The ratio of true positives to the sum of true positives and false positives, reflecting how many predicted positives are actually positive.
- **Recall (Sensitivity):** The ratio of true positives to the sum of true positives and false negatives, showing how well the model identifies actual DR cases.
- **F1-Score:** A harmonic mean of precision and recall, providing a balanced metric that considers both false positives and false negatives.

Both binary (DR vs. no DR) and multiclass classification (stages of DR severity) will be evaluated. MobileNetV2, the selected final model, achieved 98% accuracy in both tasks, with strong performance across precision, recall, and F1-score.

5. User Interface Design and Deployment

User-Friendly Interface:

The system will include an intuitive interface that allows healthcare professionals to upload retinal images and receive real-time diagnostic results. This interface will be accessible on various devices, including desktops and mobile platforms, making it adaptable for different clinical settings.

Cloud Integration and Scalability:

To ensure scalability and real-time accessibility, the system will be deployed on cloud platforms such as Google Cloud or Amazon Web Services (AWS). Cloud deployment will allow for widespread screening, particularly in underserved areas where access to eye specialists may be limited. The lightweight design of MobileNetV2 makes it ideal for real-time processing, even on mobile devices.

6. Continuous Learning and Future Improvements

Continuous Learning System:

As new retinal images are collected; the system will be designed to improve over time. New data can be used to retrain and fine-tune the model, allowing it to adapt to different populations, imaging conditions, and new DR indicators.

Future Improvements:

Further research will be conducted to improve the interpretability of the model, enabling clinicians to understand which image features the model relies on for its decisions. This will increase trust in the system and ensure that it aligns with clinical diagnostic criteria.

RESEARCH METHODOLOGY

The research methodology outlines the systematic approach adopted to develop, train, evaluate, and deploy a deep learning-based system for Diabetic Retinopathy (DR) detection and classification. The methodology is divided into key stages: dataset acquisition, image preprocessing, model development, training and validation, model evaluation, and deployment. Each stage is crucial for ensuring the accuracy and robustness of the final system.

1. Dataset Acquisition

The first step in the research involves obtaining high-quality, annotated retinal fundus images for training and testing the model. The following publicly available datasets will be used:

- **APTOS 2019 Blindness Detection Dataset** from Kaggle: A large set of retinal images classified into five categories ranging from no DR to proliferative DR.
- **Diabetic Retinopathy Detection Dataset** from Kaggle: Another large dataset containing labeled retinal images, suitable for binary and multiclass classification.

These datasets are ideal because they contain images captured under varying conditions, making the model more robust to real-world scenarios.

2. Data Preprocessing

Preprocessing is a critical step to ensure that the images are standardized and optimized for feeding into Convolutional Neural Networks (CNNs). The following techniques will be applied:

- **Resizing:** All retinal images will be resized to a uniform size (e.g., 224x224 pixels) for compatibility with the input size of various CNN architectures.
- **Normalization:** Pixel values will be scaled to the range [0, 1] to improve model convergence during training.
- **Data Augmentation:** To address the imbalance in the dataset and prevent overfitting, various data augmentation techniques such as rotation, flipping, brightness adjustment, and zooming will be applied. This ensures the model is exposed to a variety of image conditions and enhances its generalization capability.

3. Model Selection and Architecture

Several state-of-the-art deep learning models will be implemented and evaluated for their performance in detecting and classifying DR. The models include:

- **VGG16 and VGG19:** These architectures are chosen for their ability to extract complex features using deep convolutional layers.
- **ResNet50 and ResNet152V2:** The residual learning approach of ResNet allows for training very deep networks without the vanishing gradient problem, making them ideal for handling complex medical images.
- **MobileNetV2:** This lightweight architecture will be selected for the final implementation due to its efficiency and excellent performance in terms of both accuracy and computational cost. It is particularly suitable for real-time applications and mobile deployment.
- **EfficientNetB7:** This model will be tested to achieve a balance between performance and resource usage by scaling both the network depth and width.

The models will be initialized with pre-trained weights from ImageNet and then fine-tuned on the DR dataset using transfer learning techniques.

4. Training the Model

The models will be trained on the preprocessed datasets using the following approach:

- **Loss Function:** For binary classification (DR vs. no DR), binary cross-entropy will be used, while categorical cross-entropy will be applied for multiclass classification (detecting the severity levels of DR).
- **Optimizer:** Adam optimizer will be employed for its efficiency in handling sparse gradients.
- **Batch Size and Learning Rate:** Optimal batch size and learning rates will be determined through experimentation. A small learning rate with decay will ensure smooth convergence, while early stopping will be implemented to prevent overfitting.
- **Transfer Learning:** Pre-trained models (ResNet, EfficientNet, etc.) will be fine-tuned on the DR datasets. The initial layers of the network will be frozen to retain the general features learned from ImageNet, while the final layers will be retrained on the specific features of retinal images.

5. Model Validation and Evaluation

To evaluate the effectiveness of the models, several metrics will be used:

- **Accuracy:** The proportion of correctly classified images among the total number of images.
- **Precision and Recall:** Precision reflects the proportion of true positive results among the predicted positives, while recall indicates the proportion of actual positives that were correctly identified.
- **F1-Score:** The harmonic mean of precision and recall, providing a balanced evaluation metric that accounts for both false positives and false negatives.
- **Confusion Matrix:** This will be used to visualize the model's performance in terms of true positives, true negatives, false positives, and false negatives.
- **AUC-ROC Curve:** The Area Under the Receiver Operating Characteristic (ROC) curve will measure the model's ability to distinguish between classes, particularly in binary classification tasks.
- **Cross-Validation:** K-fold cross-validation will be applied to further validate the model's generalization performance.

The validation dataset will be used to fine-tune hyperparameters, while the test dataset will provide an unbiased estimate of the model's performance.

6. Comparative Analysis of Models

A comparative analysis of different deep learning models (VGG16, VGG19, ResNet50, ResNet152V2, MobileNetV2, and EfficientNetB7) will be conducted. The following aspects will be considered:

- **Accuracy:** The percentage of correctly classified images.
- **Training Time:** Time taken to train the model.
- **Model Size:** The memory and computational requirements of each model.
- **Deployment Feasibility:** How well the model performs in real-time applications and in resource-constrained environments like mobile devices.

Based on these comparisons, **MobileNetV2** will be selected as the final model due to its balance between accuracy, lightweight architecture, and deployment efficiency.

7. Deployment of the Model

The final model (MobileNetV2) will be deployed in a real-time environment through a user-friendly interface. The following steps will be taken:

- **Web and Mobile Interface:** A web-based or mobile application will be developed that allows users (such as healthcare professionals) to upload retinal images for real-time DR classification.
- **Cloud Deployment:** The model will be hosted on cloud platforms like Google Cloud or AWS to ensure scalability and accessibility across different regions.
- **Integration of API Services:** RESTful APIs will be implemented to allow seamless interaction between the user interface and the machine learning model hosted in the cloud.

8. Future Enhancements and Continuous Learning

- **Continuous Learning:** The system will incorporate a mechanism for continuous learning. As new labeled retinal images are introduced, the model will be retrained periodically to improve its accuracy and adapt to new variations in DR symptoms and imaging techniques.
- **Explainability:** Future work will focus on improving the interpretability of the model by visualizing the important features and regions in the retinal images that contribute to the classification. This will help build trust among healthcare professionals by providing a clearer rationale for the system's predictions.

CONCLUSION

This project successfully demonstrates the development of an automated system for the detection of Diabetic Retinopathy (DR) using advanced deep learning techniques. By utilizing MobileNetV2 as the final model, we achieved high accuracy in classifying fundus images for both binary and multiclass DR stages. The system aims to assist healthcare professionals in making faster and more reliable diagnoses, reducing the risk of vision loss in diabetic patients. With scalability and accessibility in mind, this system is designed for integration into clinical settings and mobile health platforms, ensuring wider reach and timely detection. The research highlights the potential of AI in transforming DR screening and contributing to more efficient healthcare solutions globally.

REFERENCES

[1] K. Ratna, A. Shedage, R. Agal, B. Maheshwari, A. Aggarwal and S. R. Goyal, "Deep Learning Approach for Detection of Diabetic Retinopathy," 2023 International Conference on Device Intelligence, Computing and Communication Technologies, (DICCT), Dehradun, India, 2023, pp. 614-618, doi: 10.1109/DICCT56244.2023.10110238.

[2] Tien Yin Wong, Tien-En Tan; The Diabetic Retinopathy “Pandemic” and Evolving Global Strategies: The 2023 Friedenwald Lecture. Invest. Ophthalmol. Vis. Sci. 2023;64(15):47. https://doi.org/10.1167/iovs.64.15.47

[3] Stela Vujosevic MD, Stephen,J Aldington HND,Paolo Silva MD, Cristina Hernández MD, Peter Scanlon MD, Tunde Peto MD, Prof Rafael Simó MD “Screening for diabetic retinopathy: new perspectives and challenges” https://doi.org/10.1016/S2213-8587(19)30411-5

[4] S. Joshi, R. Kumar, P. K. Rai and S. Garg, "Diabetic Retinopathy Using Deep Learning," 2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), Greater Noida, India, 2023, pp. 145-149, doi: 10.1109/CISES58720.2023.10183562.

[5] P. L. Gunawardhana, R. Jayathilake, Y. Withanage and G. U. Ganegoda, "Automatic Diagnosis of Diabetic Retinopathy using Machine Learning: A Review," 2020 5th International Conference on Information Technology Research (ICITR), Moratuwa, Sri Lanka, 2020, pp. 1-6, doi: 10.1109/ICITR51448.2020.9310818.

[6] S. Chaudhary and H. R. Ramya, "Detection of Diabetic Retinopathy using Machine Learning Algorithm," 2020 IEEE International Conference for Innovation in Technology (INOCON), Bangluru, India, 2020, pp. 1-5, doi: 10.1109/INOCON50539.2020.9298413.

[7] C. Jayakumari, V. Lavanya and E. P. Sumesh, "Automated Diabetic Retinopathy Detection and classification using ImageNet Convolution Neural Network using Fundus Images," 2020 International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2020, pp. 577-582, doi: 10.1109/ICOSEC49089.2020.9215270.

[8] S. Cahoon, M. Shaban, A. Switala, A. Mahmoud and A. El-Baz, "Diabetic Retinopathy Screening Using A Two-Stage Deep Convolutional Neural Network Trained on An Extremely Un-Balanced Dataset," SoutheastCon 2022, Mobile, AL, USA, 2022, pp. 250-254, doi: 10.1109/SoutheastCon48659.2022.9764079

[9] “Diabetic Retinopathy Detection” https://www.kaggle.com/c/diabetic retinopathy-detection/data

[10] “Diabetic Retinopathy 2015 Data Colored Resized” https://www.kaggle.com/datasets/sovitrath/diabetic-retinopathy-2015-data colored-resized

[11] C. A. Hartanto and A. Wibowo, "Development of Mobile Skin Cancer Detection using Faster R-CNN and MobileNet v2 Model," 2020 7th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE), Semarang, Indonesia, 2020, pp. 58-63, doi: 10.1109/ICITACEE50144.2020.9239197.

[12] Prasanna Porwal, Samiksha Pachade, Ravi Kamble, Manesh Kokare, Girish Deshmukh, Vivek Sahasrabuddhe, Fabrice Meriaudeau, April 24, 2018, "Indian Diabetic Retinopathy Image Dataset (IDRiD)", IEEE Dataport, doi: https://dx.doi.org/10.21227/H25W98

[13] Z. A. Omar, M. Hanafi, S. Mashohor, N. F. M. Mahfudz and M. Muna'im, "Automatic diabetic retinopathy detection and classification system," 2017 7th IEEE International Conference on System Engineering and Technology (ICSET), Shah Alam, Malaysia, 2017, pp. 162-166, doi: 10.1109/ICSEngT.2017.8123439.

BIBLIOGRAPHY

[1] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

[2] Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H. (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. *arXiv preprint arXiv:1704.04861*.

[3] Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. *arXiv preprint arXiv:1409.1556*.

[4] Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. *Proceedings of the 36th International Conference on Machine Learning*, 6105-6114.

[5] Kaggle. (2019). APTOS 2019 Blindness Detection Dataset. *Kaggle Datasets*. Available at: https://www.kaggle.com/c/aptos2019-blindness-detection/data.

[6] Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA*, 316(22), 2402-2410.

[7] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436-444.

[8] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. *arXiv preprint arXiv:1505.04597*.

[9] Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.