Deep Learning Architecture Model for Iris Image Segmentation in Biometrics

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Abstrak

Teknologi biometrik memanfaatkan karakteristik fisik atau perilaku manusia untuk identifikasi dan verifikasi identitas, dengan salah satu implementasi paling signifikan adalah biometrik iris. Teknologi ini menggunakan pola unik pada iris mata untuk tujuan identifikasi yang aman dan andal, namun masih menghadapi tantangan dalam memastikan segmentasi citra yang konsisten. Penelitian ini berfokus pada pengembangan segmentasi citra iris menggunakan deep learning sebagai langkah krusial dalam proses identifikasi biometrik iris. Segmentasi citra bertujuan untuk memisahkan wilayah iris dari bagian mata lainnya, seperti pupil, sklera, dan kelopak mata, namun proses ini memerlukan pendekatan yang lebih canggih untuk mengatasi variasi citra. Penelitian ini mengimplementasikan arsitektur deep learning populer, yaitu DeepLabV3 dan U-Net, untuk segmentasi citra iris. Evaluasi performa dilakukan menggunakan metrik IoU Score, Accuracy, Precision, Recall, dan F1-Score. Hasil pengujian menunjukkan bahwa DeepLabV3 memberikan kinerja terbaik dengan IoU Score sebesar 0,918, Accuracy sebesar 0,993, Precision sebesar 0,962, Recall sebesar 0,952, dan F1-Score sebesar 0,957. Keunggulan DeepLabV3 terletak pada kemampuannya dalam melakukan ekstraksi fitur yang kompleks dan menangkap konteks informasi pada berbagai skala secara efektif. Temuan ini menggarisbawahi potensi besar penerapan deep learning dalam segmentasi citra iris untuk sistem biometrik. Dengan performa optimal yang dicapai oleh DeepLabV3, teknologi ini dapat diandalkan untuk meningkatkan akurasi dan efisiensi proses identifikasi biometrik, membuka peluang luas untuk pengembangan lebih lanjut dalam aplikasi keamanan berbasis iris.

Abstract

Biometric technology is an innovation that uses human physical or behavioral characteristics for identity determination and verification with an aspect of its most significant implementations identified to be iris biometrics. The technology uses unique patterns in iris for secure and reliable identification purposes but certain challenges are encountered in ensuring consistent image segmentation. Therefore, this research focuses on developing iris image segmentation using deep learning as an important step in biometric identification process. Image segmentation aims to separate iris region from other parts of the eye, such as the pupil, sclera, and eyelids. However, the process requires a more sophisticated method to overcome image variations. This research implements popular deep learning architectures, DeepLabV3 and U-Net, for the segmentation. Subsequently, the performance of the models was evaluated based on the IoU Score, accuracy, precision, recall, and F1-score metrics. The results showed that DeepLabV3 provided the best performance with an IoU Score of 0.918, accuracy of 0.993, precision of 0.962, recall of 0.952, and F1-score of 0.957. The advantage of the model was associated with the ability to effectively extract complex features and capture information context at different scales. The observation was an indication of the significant potential possessed by deep learning applications in iris image segmentation for biometric systems. Moreover, the optimal performance achieved by DeepLabV3 showed the possibility of depending on the technology to improve the accuracy and efficiency of biometric identification process, opening up broad opportunities for further development in iris-based security applications.

1. INTRODUCTION

Biometric technology is an innovation that uses human physical or behavioral characteristics for identity determination and verification [1][2]. An example of the most significant applications of this technology is Iris Biometrics (IB) which uses the unique patterns in the iris of individuals for identification purposes [3][4]. The IB often powers the access control and identity verification systems at airports due to its extremely high accuracy. This shows that IB offers exceptional security and resistance to data manipulation, leading to the status as a primary choice in security systems [5][6]. The reliability is based on the unique and stable iris pattern which enables highly accurate long-term identification [7][8]. Moreover, the technology has become a standard in different security applications. The accuracy and efficiency of IB systems are continuously being improved through innovations in artificial intelligence (AI) technologies which open up new opportunities for further development.

AI has revolutionized several fields, including biometrics by allowing significant improvements in the accuracy and speed of identification processes [9][10]. The technology leverages machine and deep learning to analyze biometric patterns more intelligently and efficiently [11][12]. The process provides an opportunity for the automation of biometric identification and verification systems [13][14]. Moreover, AI has the capacity to improve detection accuracy and overcome challenges such as lighting and position variations [15][16]. This advantage ensures the system becomes more adaptive and responsive to different user conditions. Therefore, the role of AI is believed to be important in the evolution of more advanced and reliable biometric technology.

Segmentation is a key element in biometric identification (BI) system due to its functions in separating the iris area from other structures such as the pupil, sclera, and eyelids [17][18]. This is necessary because the accuracy level of segmentation can significantly determine the success of the entire BI system [19][20]. Several image segmentation methods have continuously focused on the improvement of accuracy and efficiency [21][22]. However, the process is limited by some challenges, such as lighting variations, image quality, as well as unpredictable eye and eyelid movements [23][24][25][26]. To overcome these obstacles, deep learning-based methods are increasingly being used because of the ability to produce more precise and robust segmentation under different conditions.

Deep learning (DL) has revolutionized iris image segmentation processes by introducing algorithms capable of capturing and analyzing complex features with high precision [27][28]. The advantage of DL lies in its ability to learn deeply from large datasets, significantly improving the quality of segmentation results. This is further strengthened by the success of models such as Convolutional Neural Networks (CNN), which have been extensively tested and reported in several research to have an outstanding performance [29][30]. DL has allowed the segmentation process to become more automated, efficient, and adaptive to existing challenges [31][32]. This method continues to open up significant opportunities to provide more robust and reliable iris segmentation systems in different applications.

DeepLabV3 and U-Net are two popular deep learning architectures in iris image segmentation. The process of DeepLabV3 is based on atrous convolution to capture broader spatial context details without losing resolution, leading to superiority in understanding subtle elements in images [33][34]. Meanwhile, U-Net has a symmetric encoder-decoder design which is very reliable in segmentation tasks [35][36]. Both have been tested on different datasets and have proven to provide solid performance in processing iris images. Each of these architectures has advantages and disadvantages but the choice often depends on the specific needs of the application. Interestingly, the combination of the two architectures is currently part of the main research topics directed toward developing superior and more precise segmentation methods.

2. LITERATURE REVIEW

IB has become an important foundation in modern security systems [37][38] due to the unique and stable pattern of iris throughout a lifetime, leading to the possibility of having an unmatched biometric identity [39][40]. The innovation related to iris recognition technology is increasing continuously in accuracy and speed as well as widespread applications. In the present time, IB supports high-level security and penetrates commercial areas, such as contactless payment mechanisms and faster healthcare services [41][42]. However, there are some major challenges, including the efforts to overcome the variations in lighting and eye position which is important to improving the performance of the system [43][44]. An example of the significant breakthroughs identified is the integration of AI, which has improved iris recognition to a higher level of reliability and efficiency.

AI is a field of computer science focused on developing machines that enable computers to interact with the world in a human-like manner [45][46]. The technology uses machine learning, pattern recognition, and natural language processing methods [47][48]. AI models learn from data to make decisions based on the information provided [49][50] and have been developed to perform complex tasks in different sectors such as health, finance, and transportation. It has also succeeded in increasing efficiency and accuracy in diverse applications. Moreover, the implementation of deep learning has been identified as an example of the development associated with the technology.

Deep Learning (DL) is a part of AI that works with artificial neural networks to process data [51]. The process focuses on imitating the processing systems of the human brain in recognizing patterns and making decisions [52][53]. DL has neurons interconnected in layers that work hierarchically [54][55] with each performing some processing and sending the results to the next [56][57]. This technology is very popular in image analysis and processing [58][59] due to the ability to learn from large image data which increases its accuracy and performance [60][61]. The innovation associated with DL is very significant, specifically in activities such as image segmentation which is now widely used in different fields [62][63].

Image segmentation is the process of separating images into parts of objects that have meaning [64][65]. This process assists in distinguishing important areas from the background in order to ensure the specific features in image can be further analyzed [66][67]. Segmentation uses algorithms to detect edges, textures, and colors in images [68][69], and has been applied in different fields, such as object recognition, medical image processing, and computer vision. However, some challenges have been identified, specifically in dealing with intensity variations and noise [70][71]. This has led to the continuous development of segmentation methods to achieve better accuracy and efficiency.

U-Net is an artificial neural network architecture specifically designed for image segmentation tasks, consisting of two main parts such as contracting and expansion paths [72]. The contracting path functions to reduce image size through convolution and pooling layers while the expansion path increases image resolution again using up-sampling and convolution [72]. U-Net is widely used in the medical field such as in MRI and CT scan image segmentation [73][74]. Architecture of the network performs learning process through image annotation to produce accurate segmentation as presented in Figure 1 [75][76]. The development of U-Net has led to significant progress in medical image analysis and processing.

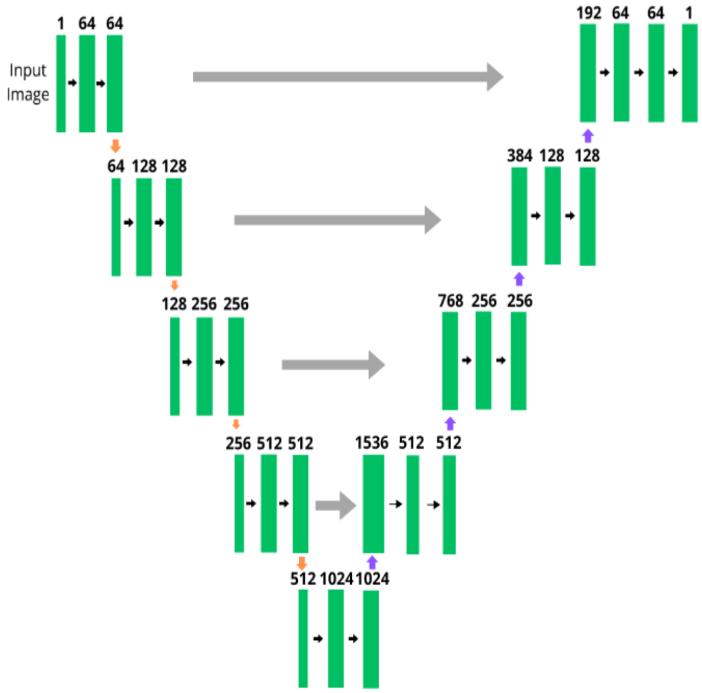

Figure 1. U-Net Architecture

Another highly effective artificial neural network model in image segmentation is DeepLabV3 [77]. The model uses atrous convolution methods, which can expand the range of filters without reducing spatial resolution, to ensure better capturing of context at different scales in images [78][79]. Moreover, DeepLabV3 has been widely used in different applications, from object recognition to medical image analysis, leading to significant improvements in the accuracy and efficiency of the segmentation process [79]. The architecture of DeepLabV3 is presented in the following Figure 2.

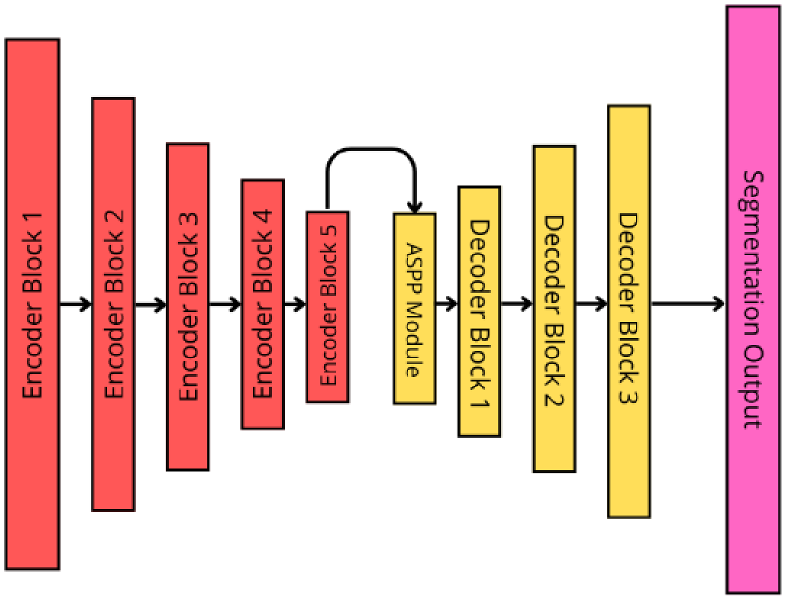

Figure 2. DeepLabV3 Architecture

Image segmentation testing has become an important topic in digital image processing research, with different evaluation metrics developed and applied to assess the performance of segmentation models. Some of these metrics include Intersection over Union (IoU), accuracy, precision, recall, and f1-score [80][81]. IoU measures the overlap between predicted and ground truth segmentation to show the proportion of segmented regions out of the total combined area [82]. Meanwhile, accuracy is the proportion of total correct predictions [83], precision measures the proportion of correct positive predictions [83], recall calculates the proportion of total relevant data successfully detected [83], and F1-score provides a balance between precision and recall [83].

$$IoU\ Score = \frac{TP}{TP+FN+FP} \tag{1}$$

Description:
TP = True Positive
FN = False Negative
FP = False Positive

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \tag{2}$$

Description:
TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

Description:
TP = True Positive
FN = False Negative

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

Description:
TP = True Positive
FP = False Positive

$$F1 - Score = 2 * \frac{Precision\ x\ Recall}{Precision + Recall} \tag{5}$$

3. METHODOLOGY

3.1. *Materials*

The MMU-Dataset (Multimedia University Iris Database) is a dataset designed for iris recognition technology research and development [84]. It includes data on 45 subjects with each consisting of multiple images of both eyes taken under different lighting conditions and shooting angles to increase variation and challenge in the analysis. The diversity of image acquisition conditions in the dataset allows testing and validation of iris recognition algorithms in different situations, leading to the significance of the database as a valuable resource for biometric research community. The MMU-Dataset is presented in the following Figure 3.

Figure 3. MMU-Dataset

3.2. *Methods*

Iris image segmentation is developed using deep learning to improve the reliability and accuracy of biometric recognition systems. Therefore, this research focused on a deeper analysis of iris patterns and characteristics used as the basis for decision-making in security and personal identification applications. The aim was to produce an accurate and efficient segmentation method capable of accelerating iris recognition process and improving reliability. This was achieved through a comprehensive methodological framework for iris image segmentation, including dataset collection, data augmentation, deep learning architecture selection, image segmentation training, image segmentation testing, and analysis of evaluation results as presented in the flowchart in Figure 4.

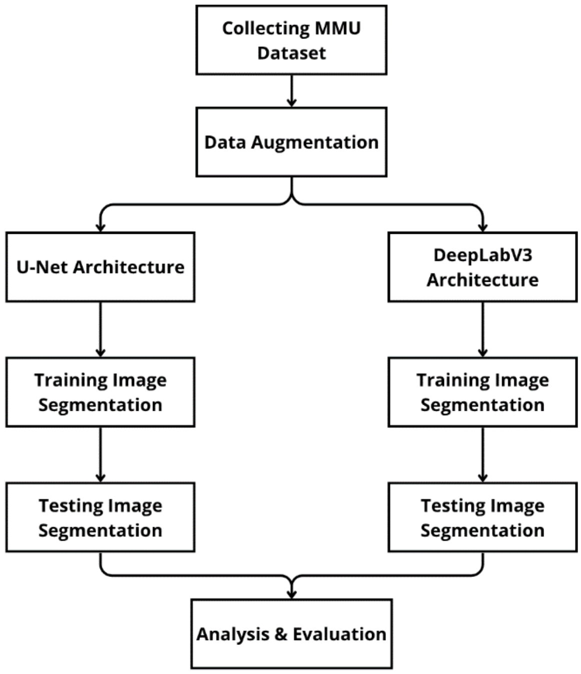

Figure 4. Research Flowchart

The process was initiated by collecting iris image data from different sources at different lighting conditions, resolutions, and viewing angles [84]. This was conducted to ensure sufficient data diversity in training the model to adapt to diverse real-world conditions [23]. After the data were collected, an augmentation process was applied to improve the robustness and generalization of the model.

The augmentation can be achieved through different methods capable of modifying the original image to produce more diverse variations [85]. An example of the method is scalation which adjusts image size to uniform dimensions [86] and the process is considered important for the consistency of input into the model in order to facilitate training and improve performance. Data augmentation methods can assist in enriching the dataset, reducing overfitting, and enhancing the generalization ability of the model [87].

Several types of DL architectures can be used for iris image segmentation tasks. However, U-Net was selected due to the ability to produce precise segmentation with up-sampling layers capable of assisting to reconstruct image details [88]. DeepLabV3 was also selected due to the capacity to handle scale variations and capture multi-scale context through atrous convolution [79]. These architectures were trained using augmented data and the model was tested with new data to evaluate the performance after training. The metrics, accuracy, precision, recall, f1-score, and IoU, were applied to assess the ability of the model to detect and separate iris from the rest of the eye [80][81]. Moreover, the evaluation results were analyzed to identify the strengths and weaknesses of each model, including performance comparisons based on the metrics and visual observation of the segmentation results.

4. RESULTS & DISCUSSION

Iris image segmentation was evaluated to determine the optimal performance of different architectures tested with a focus on hyperparameter adjustments for each method used. The hyperparameter adjustments were focused on learning rate, batch size, and optimizer [89][90]. Learning rate hyperparameter was tested to determine the optimal value that ensured architecture learned efficiently without experiencing overfitting or underfitting. A higher learning rate can speed up training but risks missing the optimal solution while a lower value is capable of slowing down convergence. Batch size adjustment was also important to optimize GPU memory usage and training stability where a larger value reduced fluctuations in gradient updates but required more memory. Moreover, the selection of the right optimizer was important because algorithms such as Adam, SGD, and RMSProp could produce different results depending on architecture and data used.

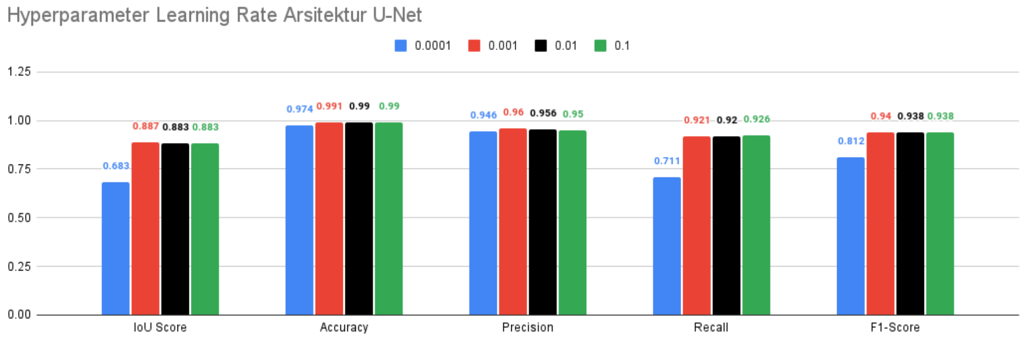

Figure 5. Learning Rate Hyperparameter of U-Net Architecture

Table 1. Learning Rate Hyperparameter of U-Net Architecture

Learning Rate	*IoU Score*	*Accuracy*	*Precision*	*Recall*	*F1-Score*
0.0001	*0.683*	*0.974*	*0.946*	*0.711*	*0.812*
0.001	*0.887*	*0.991*	*0.96*	*0.921*	*0.94*
0.01	*0.883*	*0.99*	*0.956*	*0.92*	*0.938*
0.1	*0.883*	*0.99*	*0.95*	*0.926*	*0.938*

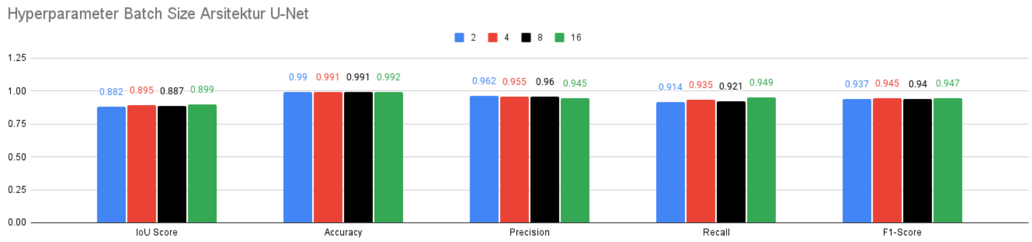

Figure 6. Batch Size Hyperparameter of U-Net Architecture

Table 2. Batch Size Hyperparameter of U-Net Architecture

Batch	IoU Score	Accuracy	Precision	Recall	F1-Score
2	*0.882*	*0.99*	*0.962*	*0.914*	*0.937*
4	*0.895*	*0.991*	*0.955*	*0.935*	*0.945*
8	*0.887*	*0.991*	*0.96*	*0.921*	*0.94*
16	*0.899*	*0.992*	*0.945*	*0.949*	*0.947*

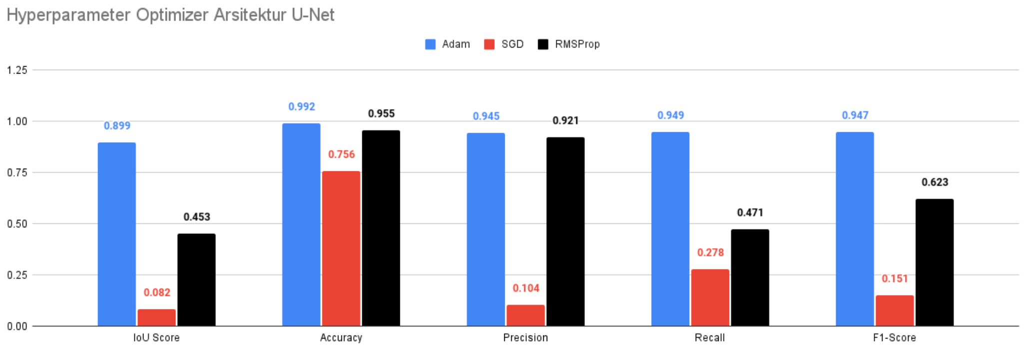

Figure 7. Optimizer Hyperparameter of U-Net Architecture

Table 3. Optimizer Hyperparameter of U-Net Architecture

Optimizer	IoU Score	Accuracy	Precision	Recall	F1-Score
Adam	0.899	0.992	0.945	0.949	0.947
SGD	0.082	0.756	0.104	0.278	0.151
RMSProp	0.453	0.955	0.921	0.471	0.623

Figure 5 and Table 1 show that the variation in learning rate hyperparameters of the U-Net architecture leads to different results on the evaluation metrics. Learning rate of 0.0001 produced an IoU Score of 0.683, accuracy of 0.974, precision of 0.946, recall of 0.711, and f1-score of 0.812 while 0.001 had the highest performance with 0.887, 0.991, 0.96, 0.921, and 0.94 respectively. It was also observed that learning rate of 0.01 had good results with 0.883, 0.99, 0.956, 0.92, and 0.938, and learning rate of 0.1 showed almost the same performance with 0.883, 0.99, 0.95, 0.926, and 0.938 respectively. The trend showed that a 0.001 learning rate had the best results on several evaluation metrics followed by 0.01 and 0.1 while 0.0001 had lower values.

Figure 6 and Table 2 show that the variation in batch sizes of the U-Net architecture leads to different performance on evaluation metrics. This was observed from the fact that batch size 2 had an IoU Score of 0.882, accuracy of 0.99, precision of 0.962, recall of 0.914, and f1-score of 0.937 while batch size 4 recorded 0.895, 0.991, 0.955, 0.935, and 0.945, batch size 8 had 0.887, 0.991, 0.96, 0.921, and 0.94, and batch size 16 had the best performance with 0.899, 0.992, 0.945, 0.949, and 0.947 respectively. These results showed that larger batch sizes tended to provide better results with batch size 16 having the best performance on several evaluation metrics.

Figure 7 and Table 3 show that the optimizer hyperparameter of the U-Net architecture provides significant performance on different evaluation metrics. The Adam optimizer was the best with an IoU Score of 0.899, accuracy of 0.992, precision of 0.945, recall of 0.949, and f1-score of 0.947. The RMSProp optimizer showed moderate results with 0.453, 0.955, 0.921, 0.471, and 0.623 respectively. Meanwhile, the SGD optimizer had the lowest with 0.082, 0.756, 0.104, 0.278, and 0.151 respectively. The results showed that the use of the Adam optimizer significantly improved the performance of the U-Net model compared to other optimizers, leading to the preference as the best choice for image segmentation task in this research.

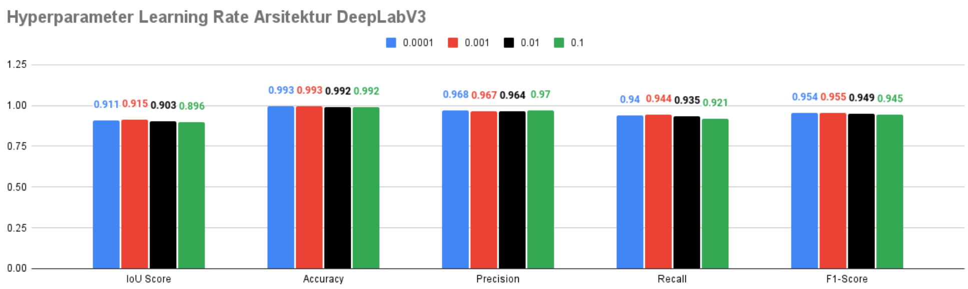

Figure 8. Learning Rate Hyperparameter of DeepLabV3 Architecture

Table 4. Learning Rate Hyperparameter of DeepLabV3 Architecture

Learning Rate	*IoU Score*	*Accuracy*	*Precision*	*Recall*	*F1-Score*
0.0001	*0.911*	*0.993*	*0.968*	*0.94*	*0.954*
0.001	*0.915*	*0.993*	*0.967*	*0.944*	*0.955*
0.01	*0.903*	*0.992*	*0.964*	*0.935*	*0.949*
0.1	*0.896*	*0.992*	*0.97*	*0.921*	*0.945*

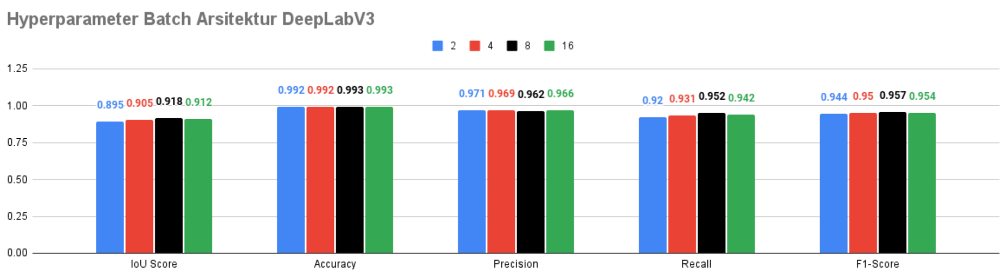

Figure 9. Batch Hyperparameter of DeepLabV3 Architecture

Table 5. Batch Hyperparameter of DeepLabV3 Architecture

Batch	IoU Score	Accuracy	Precision	Recall	F1-Score
2	0.895	0.992	0.971	0.92	0.944
4	0.905	0.992	0.969	0.931	0.95
8	0.918	0.993	0.962	0.952	0.957
16	0.912	0.993	0.966	0.942	0.954

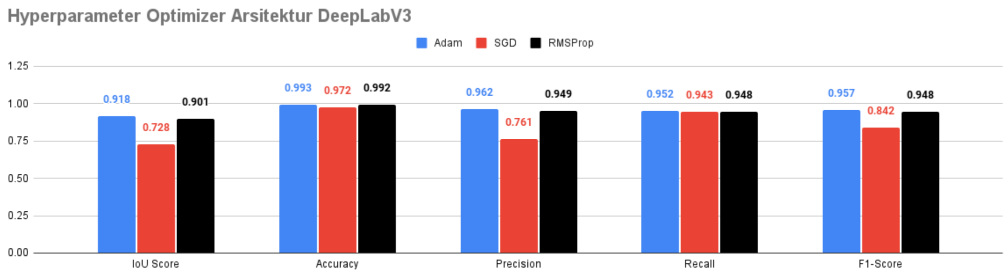

Figure 10. Optimizer Hyperparameter of DeepLabV3 Architecture

Table 6. Optimizer Hyperparameter of DeepLabV3 Architecture

Optimizer	*IoU Score*	*Accuracy*	*Precision*	*Recall*	*F1-Score*
Adam	*0.918*	*0.993*	*0.962*	*0.952*	*0.957*
SGD	*0.728*	*0.972*	*0.761*	*0.943*	*0.842*
RMSProp	*0.901*	*0.992*	*0.949*	*0.948*	*0.948*

Figure 8 and Table 4 show that the variation in learning rates of DeepLabV3 architecture produces different performances on the evaluation metrics. Learning rate of 0.0001 produced an IoU Score of 0.911, accuracy of 0.993, precision of 0.968, recall of 0.94, and f1-score of 0.954 while a 0.001 rate had slightly better results with 0.915, 0.993, 0.967, 0.944, and 0.955, learning rate of 0.01 also recorded 0.903, 0.992, 0.964, 0.935, and 0.949 respectively. It was further observed that learning rate of 0.1 showed good performance with an IoU Score of 0.896, accuracy of 0.992, precision of 0.97, recall of 0.921, and f1-score of 0.945. The results showed that learning rate of 0.001 provided the best overall performance for different evaluation metrics, leading to the designation as the optimal choice for DeepLabV3 architecture in this research.

Figure 9 and Table 5 show that different batch sizes of DeepLabV3 architecture produce varying results on the evaluation metrics. For example, batch size 2 had an IoU Score of 0.895, accuracy of 0.992, precision of 0.971, recall of 0.92, and f1-score of 0.944 while batch size 4 showed an improvement with 0.905, 0.992, 0.969, 0.931, and 0.95, batch size 8 recorded the most optimal performance with 0.918, 0.993, 0.962, 0.952, and 0.957, and batch size 16 had 0.912, 0.993, 0.966, 0.942, and 0.954 respectively. The results showed that batch size 8 provided optimal results based on different evaluation metrics and this showed the tendency of having the best performance at larger sizes.

Figure 10 and Table 6 show that the adoption of different optimizers in DeepLabV3 architecture leads to different performance on evaluation metrics. The Adam optimizer had the best results with an IoU Score of 0.918, accuracy of 0.993, precision of 0.962, recall of 0.952, and f1-score of 0.957 while the RMSProp optimizer showed quite good performance with 0.901, 0.992, 0.948, 0.948, and 0.948 and the SGD optimizer had the lowest by recording 0.728, 0.972, 0.761, 0.943, and 0.842 respectively. The results showed that the Adam optimizer significantly improved the performance of DeepLabV3 architecture compared to other optimizers, leading to the designation as an optimal choice for image segmentation task in this research.

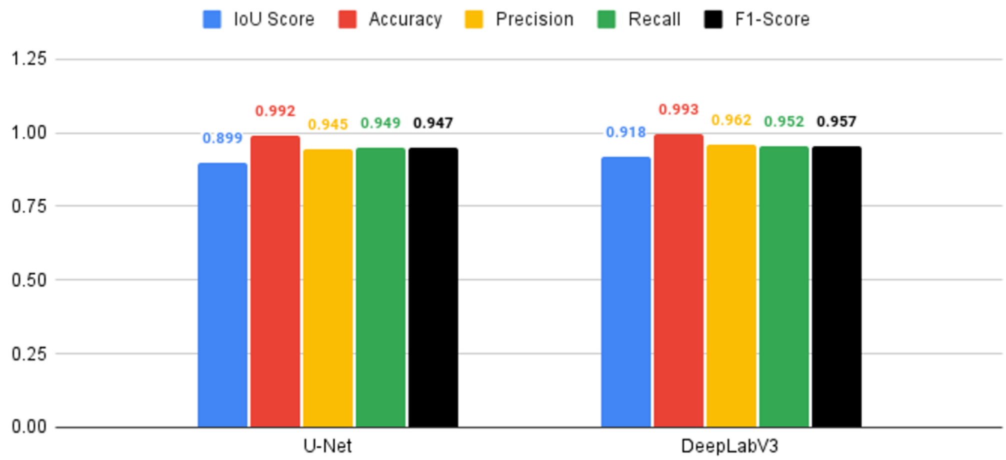

Figure 11. Main Architecture Evaluation Results

Table 7. Architecture Evaluation Results

Architecture	*IoU Score*	*Accuracy*	*Precision*	*Recall*	*F1-Score*
Caht [91]	*0.807*	-	-	-	*0.765*
Wahet [91]	*0.809*	-	-	-	*0.895*
FCN32-VGG16 [92]	*0.817*	*0.94*	*0.911*	*0.887*	-
U-Net	*0.899*	*0.992*	*0.945*	*0.949*	*0.947*
DeepLabV3	*0.918*	*0.993*	*0.962*	*0.952*	*0.957*

Figure 11 and Table 7 show that the U-Net and DeepLabV3 architectures have competitive performance on the main evaluation metrics. This was observed from the fact that the U-Net architecture produced an IoU Score of 0.899, accuracy of 0.992, precision of 0.945, recall of 0.949, and f1-Score of 0.947 while DeepLabV3 architecture showed slightly superior performance with 0.918, 0.993, 0.962, 0.952, and 0.957 respectively. The analysis showed that both architectures had good results, but DeepLabV3 was superior in terms of precision and recall, leading to the preference as a more optimal choice for the image segmentation task in the context of this research. Compared to previous methods such as Caht and Wahet, which rely on non-learning-based techniques, U-Net and DeepLabV3 benefit from data-driven feature learning that enables better adaptability to complex image patterns. Even when compared to earlier deep learning models like FCN32-VGG16, which lacks decoder refinement and multi-scale feature aggregation, U-Net and DeepLabV3 demonstrate superior segmentation accuracy due to their more advanced architectural designs.

5. CONCLUSION

In conclusion, the U-Net architecture hyperparameters had the best results with learning rate of 0.001, a batch of 16, as well as an Adam optimizer that recorded an IoU Score of 0.899, accuracy of 0.992, precision of 0.945, recall of 0.949, and f1-score of 0.947. DeepLabV3 architecture hyperparameters obtained the best results with learning rate of 0.001, a batch of 8, as well as an Adam optimizer that recorded an IoU Score of 0.918, accuracy of 0.993, precision of 0.962, recall of 0.952, and f1-score of 0.957. The performance of DeepLabV3 was superior due to the ability to perform better feature extraction in capturing information context at different scales such as fine details in small objects, structural characteristics in medium-sized objects, and the global overall spatial context of image. The results showed that DeepLabV3 architecture was the most optimal choice for iris segmentation on the MMU-Dataset.

Future research can explore modifications to DeepLabV3 or try other architectures to push the limits of iris segmentation performance. Moreover, DeepLabV3 architecture can be explored by developing modifications to the contracting or expansion path regions. Future iris segmentation development can also be applied by adding other iris datasets to enrich the variety of data for training with DL.

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