KOMTEKINFO JOURNAL
LPPM Universitas Putra Indonesia YPTK Padang
Jl. Raya Lubuk Begalung, Padang, West Sumatera, Indonesia, Zip Code: 25221
Volume: 12, Issue: 3, Page: 183 - 190, September 30th, 2025, e-ISSN: 2502-8758
Available online at website: https://jkomtekinfo.org/ojs/index.php/komtekinfo

Implementation of Skin Diseases in Toddlers Using Convolutional Neural Networks

Dian Maharani✉, Y. Yuhandri , Jhon Veri
[1]Magister Teknik Informatika, Ilmu Komputer, Universitas Putra Indonesia YPTK, Padang, 25221, Indonesia
[2]Magister Teknik Informatika, Ilmu Komputer, Universitas Putra Indonesia YPTK, Padang, 25221, Indonesia
[3]Magister Teknik Informatika, Ilmu Komputer, Universitas Putra Indonesia YPTK, Padang, 25221, Indonesia

dian.maharani1991@gmail.com

Abstrak

The development of Artificial Intelligence (AI) technology, particularly in the field of computer vision, has made a significant contribution to medical image analysis. Skin disease in toddlers is a common health problem, especially in developing countries. Toddlers' skin is highly susceptible to various infections and dermatological conditions, ranging from bacterial and viral infections to allergies. Some skin diseases frequently found in toddlers include eczema, dermatitis, impetigo, and fungal infections. This study aims to develop a skin disease classification system in toddlers using the Convolutional Neural Network (CNN) method that can be implemented in applications. The Convolutional Neural Network (CNN) method and the U-Net architecture are used to identify skin diseases in toddlers, requiring a fast and accurate diagnosis, but limited medical personnel and examination time are challenges. A deep learning-based system is proposed to assist the automatic identification process. The research dataset consists of 100 toddler skin images obtained from Siti Rahmah Islamic Hospital, covering various types of common skin diseases. The preprocessing process includes cropping, resizing to 128x128 pixels, normalization, and data augmentation to increase the diversity of the dataset. The CNN architecture is used in the feature extraction stage through convolution and pooling layers, while the U-Net is applied in the segmentation stage to separate the wound area from healthy skin with high precision through the encoder-decoder mechanism and skip connection. The model is trained using the Adam optimization algorithm with the Binary Cross-Entropy loss function and the accuracy evaluation metric and Mean Intersection over Union (IoU). The results show that the system is able to segment the wound area with 95.7% accuracy on the test data, and produces fast and efficient detection. The application of the CNN and U-Net methods in this study proves its effectiveness in supporting the medical diagnosis process, especially in cases of toddler skin diseases, as well as can be a reference in contributing to improving the quality of health services, especially in the diagnosis of skin diseases in toddlers and the development of computer vision-based decision support systems in the health sector.

Keywords: CNN, U-Net, image segmentation, toddler skin disease, deep learning

1. Introduction

Advances in Artificial Intelligence technology have opened up new opportunities in the health sector, especially in medical image processing[1]. Convolutional Neural Network (CNN) is one of the effective methods for extracting visual features from skin images, such as color, texture, and lesion patterns[2]. The U-Net architecture, specifically designed for medical image segmentation, is highly effective in separating healthy skin areas from lesioned areas even on limited datasets[3].

In the medical field, CNN have been successfully applied in various tasks such as tumor detection, skin lesion classification, and identification of abnormalities in radiographs[4]. Skin disease in toddlers is one of the most common medical problems, especially in developing countries[5]. This condition requires a fast and accurate diagnostic approach, considering that toddlers' skin is very susceptible to various dermatological infections[6].

Skin disease is a common health problem in toddlers, especially because their immune system is not yet mature, making them more susceptible to infection and irritation[6]. Environmental conditions, hygiene, and genetic factors also influence this susceptibility. Some skin conditions commonly found in toddlers include atopic dermatitis, impetigo, diaper rash, and fungal infections[7]. A quick and accurate diagnosis is essential to prevent complications[8], However, limited medical personnel, examination time, and symptom variations often pose obstacles.

Developments in artificial intelligence technology offer opportunities to assist in the disease identification process[9] skin automatically, quickly, and accurately. The conventional process of diagnosing skin diseases still relies on visual observation by medical personnel[10]. The limited number of pediatric dermatologists, the high number of patients, and limited consultation time are challenges in providing a fast and accurate diagnosis[11].

Skin infections rank third out of ten diseases among short-term patients of Indonesian emergency clinics, as shown by the 2010 Indonesian Welfare Profile information[12]. Treatment therapy is usually administered to patients through medication. Correct medication administration and dosage are crucial for treating skin diseases and require a standardized knowledge of pharmacology[13]. Incorrect dosage will cause health problems, such as increased side effects, treatment failure, and resistance[14].

Several previous studies have applied Deep Learning methods, especially Convolutional Neural Network (CNN), to detect skin diseases[2] developed a CNN-based skin cancer classification system with 75% accuracy, demonstrating the potential of CNN in pattern recognition in medical images.[15] implemented a web-based CNN for common skin disease classification, but the validation accuracy only reached 58% due to dataset limitations. Meanwhile, [16] applied CNN with Adam optimizer and low learning rate to detect skin diseases, successfully achieved 97% accuracy but did not discuss lesion area segmentationFurthermore, research conducted by [17], This research focuses on Artificial Intelligence (AI) to assist doctors and provide an efficient alternative solution for diagnosing patients, whether they have TB or not, more quickly. The testing phase yielded an accuracy value of 99.29% in scenario 1 and 97.67% in scenario 2. Other research conducted by[18] stated that this study aimed to analyze the performance of an image classification model for lung disease detection using the long short-term memory (LSTM) deep learning method, and to compare it with other methods such as convolutional neural networks (CNN). The test results showed that the CNN model achieved 92.5% accuracy in classifying lung X-ray images as normal or abnormal. This model also demonstrated 90.8% precision and 89.7% recall. In a study conducted by[19], A cataract detection system using a Convolutional Neural Network (CNN) method has been designed to significantly assist doctors in the initial cataract screening process. The system analyzes cataract images with 96% accuracy in detecting the presence of cataracts. [20], CNN to classify papaya ripeness by color, managed to achieve an accuracy of 96%. [21], image classification in the identification of lime and mandarin oranges by applying CNN, successfully achieved 100% accuracy.

Although various previous studies have successfully applied CNN in skin disease classification, studies that specifically use CNN with U-Net architecture optimization for disease identification[22] Skin research in toddlers is still limited. Furthermore, previous research has focused more on adult populations, while studies focusing on toddlers are scarce. This includes the unique physical conditions of toddlers, varying image quality due to lighting and movement, and the unique skin conditions typical of toddlers, This presents a unique challenge that has not been fully addressed in previous research. Therefore, there is a need to develop a more specific and optimized CNN model using the U-Net architecture to improve the accuracy of diagnosing skin diseases in toddlers.

Most studies focus on whole-image classification without detailed lesion location mapping. This approach can reduce diagnostic accuracy because the lesion area is not isolated from the background of healthy skin. This study aims to address this gap by combining a CNN for feature extraction and a U-Net for pixel-by-pixel segmentation, enabling precise identification and separation of skin lesions in toddlers.

2. Methods

This research methodology is systematically explained and serves as a guideline for conducting research. This study uses Deep Learning methods with a combination of Convolutional Neural Network (CNN) and U-Net architectures to identify skin diseases in toddlers. This research is described in a framework, and the researchers will outline the stages of this framework.

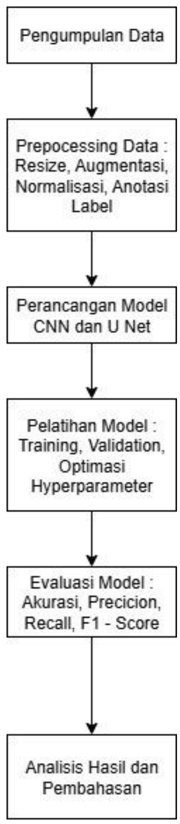

Figure 1 Framework

2.1 *Dataset*

The collected data consists of digital images of skin diseases in toddler patients. The data acquisition process involved taking direct photographs of skin areas indicated as having abnormalities, covering several common conditions such as eczema, prickly heat, diaper rash, and scabies. The dataset consists of 100 toddler skin images collected from Siti Rahmah Islamic Hospital. The images cover various types of common skin diseases in toddlers, obtained in JPEG and PNG formats. All data has been anonymized to maintain patient confidentiality.

2.2 Preprocessing *Data*

Image data is preprocessed to ensure image quality meets analysis standards. This process includes:

1. Crop : Extracting specific portions of the image relevant to disease detection.
2. Resize : Resizing the image to 128x128 pixels to facilitate computer analysis.
3. Augmentasi Data : Increasing the size of the dataset through rotation, horizontal shifting, flipping, and scaling techniques to prevent overfitting and improve model generalization.
4. Anotasi label : The process of adding labels or additional information to data, such as images, videos, or text, to provide more information about the data. In machine learning, label annotation allows models to learn and recognize patterns in the data, thus making accurate predictions.

2.3 CNN and U-Net Model Design

The development of a CNN model using the U-Net architecture is used as the basis for identifying and classifying skin diseases in toddlers. The developed CNN architecture consists of several main layers:

1. Convolution Layer : Extracts important features from the image.
2. Pooling Layer : Reduces the size of the convolutional image for computational efficiency.
3. Fully Connected Layer : Performs the final classification based on the extracted features.
4. Dropout Layer : Prevents overfitting by randomly removing neurons in the network during training.

2.4 Model Training

Training and Validation The model is trained using the Stochastic Gradient Descent (SGD) optimization algorithm with the parameters set as follows:

1. Batch size : 32 images per iteration.
2. Epoch : 50 complete iterations over the entire dataset.
3. Learning rate : 0.001 to stabilize the optimization process.

2.5 Model Performance Evaluation

The evaluation was conducted using a confusion matrix to quantitatively measure the model's accuracy. The following parameters were used to measure success:

$$Accuracy\ (\%) = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) \times 100\% \quad (1)$$

$$Precision\ (\%) = \left(\frac{TP}{TP+FP}\right) \times 100\% \quad (2)$$

$$Recall\ (\%) = \left(\frac{TP}{TP+FN}\right) \times 100\% \quad (3)$$

$$F1\ Score\ (\%) = \left(\frac{2 \times Precision \times Recall}{Precision+Recall}\right) \times 100\% \quad (4)$$

3. Results and Discussions

The process of implementing a toddler skin disease identification system at Siti Rahmah Hospital begins with feature extraction using a convolution layer that applies a matrix multiplication operation between the filter kernel and the image region to produce feature maps, then continues with a pooling layer to reduce spatial dimensions for computational efficiency.

The segmentation stage is performed using a U-Net architecture consisting of an encoder and a decoder. The final section uses a fully connected layer and a softmax activation function to calculate the probability of a pixel being classified as a wound or non-wound. The model training process is performed by iteratively optimizing weights using the backpropagation algorithm with gradient descent to minimize the loss function. Final system evaluation includes performance measurements using accuracy, precision, and recall metrics on test data, as well as inference time analysis to ensure readiness for real-time implementation to support clinical diagnosis.

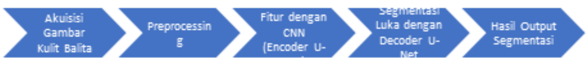

Figure 2 System Analysis Stages

Based on Figure 2 above, the analysis stages for the toddler skin disease identification system are designed through three integrated core layers:

1. The Input and Preprocessing Layer, which receives images of toddler skin and performs normalization and image size adjustment to ensure uniformity of the input data.
2. The Feature Extraction Layer, consisting of two convolution and pooling blocks, is used to extract texture, color, and edge patterns that reflect the characteristics of wounds on toddler skin.
3. The Segmentation Layer, which classifies each pixel in the image using a U-Net decoder to generate a segmentation map that precisely marks the wound area.

3.1. Input Images

The data used in this study were images of toddlers' skin showing signs of skin disease. These images were obtained from medical documentation or visual records of patients who had previously undergone examinations, and therefore were considered historical patient data.

Table 1. Input Image

Picture	Skin Diases
	Dyshidrotic eczema
	Nummular eczema

Based on Table 1 above, the input image represents a patient with the following diseases :

1. Dyshidrotic eczema (also called pompholyx or dyshidrosis) is a form of chronic eczema characterized by the appearance of small, fluid-filled blisters on the palms of the hands, fingers, and sometimes the soles of the feet.
2. Nummular eczema (also called nummular dermatitis or discoid eczema) is a form of chronic eczema characterized by round or oval coin-shaped skin lesions.

3.2. Masking Data

In computer vision, particularly in image segmentation tasks, the data masking process is a crucial step that serves as a ground truth representation. Data masking is achieved by creating a pixel-wise map of the image, distinguishing between the target object (e.g., a skin wound) and the background.

Table 2.Masking Data

Picture	Masking Picture
	
	

3.3 Cropping

To ensure optimal skin disease identification results, image cropping and focusing on the skin area of the original image are performed. This process aims to remove irrelevant background and narrow the CNN model's search space to only the important parts, namely the skin areas that potentially show disease symptoms. By focusing on these areas, the system can reduce visual noise and improve feature extraction accuracy, as only relevant information is processed in subsequent stages. This technique also helps speed up inference by reducing the input image dimensionality without sacrificing required data quality.

Table 3.Croping

Picture	Cropping Picture
	
	

3.4 Rotation

Rotation is a data augmentation technique that involves rotating images of toddler skin at specific angles, such as 90°, 180°, or 270°. This technique aims to introduce variations in the visual orientation of skin disease symptoms into the training data, allowing the Convolutional Neural Network (CNN) model to learn to recognize disease characteristics from various perspectives.

Table 4.Rotation

Picture	Rotation 90°	Rotation 180°	Rotation 270
			
			

3.5 Data Preprocessing Results

The preprocessing process successfully converted all 100 toddler skin images into a uniform 128x128 pixel format. Data augmentation increased the training dataset to 500 images through rotation, flipping, and zooming techniques. The cropped images revealed more focused lesion areas, making it easier for the model to detect patterns and textures.

3.6 Model Training Results

The CNN–U-Net model was trained for 50 epochs, with 80% of the data allocated for training and 20% for testing. The Adam optimizer with a learning rate of 0.001 was used to accelerate model convergence. The training and validation loss graphs show a consistent decrease until the 35th epoch, then stabilize until the end of training, indicating minimal overfitting.

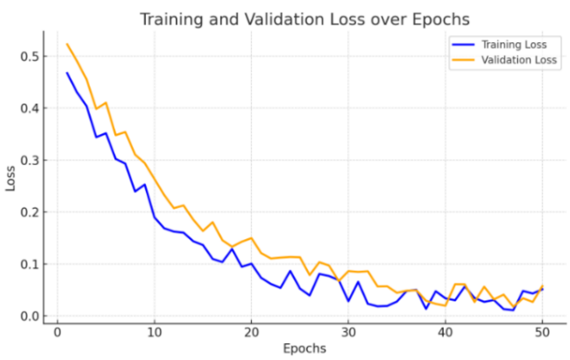

Figure 3 Training and Validation Loss

3.7 The results of the performance evaluation of the CNN and U Net models:

Table 5. Performance Metrics

Metric	Value (%)
Akurasi	95,7
Presisi	94,3
Recall	96,8
Mean IoU	92,5

4. Conclusions

This research successfully developed a skin disease identification system for toddlers based on a Convolutional Neural Network with a U-Net architecture for medical image segmentation. Utilizing 100 toddler skin images from Siti Rahmah Islamic Hospital, the proposed model achieved 95.7% accuracy, 94.3% precision, 96.8% recall, and 92.5% Mean Intersection over Union (IoU).

These results demonstrate that the integration of CNN for feature extraction and U-Net for segmentation is effective in separating lesion areas from healthy skin, even on a limited dataset. The model's high performance demonstrates its potential application in supporting real-time medical diagnostic processes in clinical settings, particularly in assisting medical personnel in quickly and accurately identifying skin diseases in toddlers. This research also contributes to the development of Artificial Intelligence-based decision support systems in the field of pediatric health. With further optimization and dataset expansion, this system has the potential for widespread use in healthcare facilities.

References

[1] N. S. Irjanto, R. H. Kiswanto, I. S. Sabra, dan F. Rahman, "Sistem Pengenalan Penyakit Kulit Berbasis Computer Vision Dengan Metode Convolutional Neural Network (CNN)," *Techno.Com*, vol. 23, no. 3, hal. 716–728, 2024, doi: 10.62411/tc.v23i3.11355.

[2] L. Hakim, Z. Sari, dan Handhajani, "Klasifikasi Citra Pigmen Kanker Kulit Menggunakan Convolutional Neural Network," *J. RESTI*, vol. 5, no. 2, hal. 379–385, 2021, doi: 10.29207/resti.v5i2.3001.

[3] T. Naraloka, L. I. Kesuma, A. Sukmawati, dan M. Cristianti, "Arsitektur U-Net pada Segmentasi Citra Hati sebagai Deteksi Dini Kanker Liver," *Techno.Com*, vol. 21, no. 4, hal. 753–764, 2022, doi: 10.33633/tc.v21i4.6669.

[4] D. Gunawan dan H. Setiawan, "Convolutional Neural Network dalam Citra Medis," *KONSTELASI Konvergensi Teknol. dan Sist. Inf.*, vol. 2, no. 2, hal. 376–390, 2022, doi: 10.24002/konstelasi.v2i2.5367.

[5] R. Gustia, S. W. Yenny, dan S. Octari, "Karakteristik

penyakit kulit pada anak di poliklinik kulit dan kelamin RSUP. Dr. M. Djamil Padang periode 2016-2018," *J. Kedokt. Syiah Kuala*, vol. 20, no. 3, 2020, doi: 10.24815/jks.v20i3.18277.

[6] A. N. Mario *dkk.*, "Anatomical and Physiological Characteristics of Neonatal and Infant Skin: Effects on Immunity and Dermatitis Prevalence," *J. Biol. Trop.*, vol. 24, no. 1b, hal. 173–180, 2024, doi: 10.29303/jbt.v24i1b.7918.

[7] M. D. A. Putra, A. D. Baihaqie, dan A. Irawan, "Sistem Pakar Diagnosa Penyakit Kulit pada Manusia dengan Menerapkan Metode Forward Chaining," *J. Ris. dan Apl. Mhs. Inform.*, vol. 5, no. 2, hal. 325–332, 2024, doi: 10.30998/jrami.v5i2.9191.

[8] D. Supiyan, "Pengembangan Sistem Pakar Untuk Diagnosa Penyakit Diabetes Melitus Menggunakan Metode Forward Chaining," *bit-Tech*, vol. 7, no. 3, hal. 918–927, 2025, doi: 10.32877/bt.v7i3.2244.

[9] Siti Masrichah, "Ancaman Dan Peluang Artificial Intelligence (AI)," *Khatulistiwa J. Pendidik. dan Sos. Hum.*, vol. 3, no. 3, hal. 83–101, 2023, doi: 10.55606/khatulistiwa.v3i3.1860.

[10] M. R. Febrianto, "Pemanfaatan Artificial Intelligence Untuk Mengidentifikasi Dan Mengatasi Masalah Kesehatan Kulit Wajah," *Pros. Semin. Nas. Sains dan Teknol. SainTek"*, vol. 2, no. 1, hal. 712–720, 2025.

[11] G. F. Tarimakase, A. Gunaryati, dan S. Ningsih, "Sistem Pakar Diagnosis Penyakit Kulit Balita Menggunakan Metode Certainty Factor dan Forward Chaining," *STRING (Satuan Tulisan Ris. dan Inov. Teknol.*, vol. 8, no. 1, hal. 120, 2023, doi: 10.30998/string.v8i1.16469.

[12] R. Rismanto, Y. Yunhasnawa, dan M. JIFTI, "Pengembangan Sistem Pakar Untuk Diagnosa Penyakit Kulit Pada Manusia Menggunakan Metode Naive Bayes," *J. Ilm. Teknol. Inf. dan Robot.*, vol. 1, no. 1, hal. 18–24, 2019, doi: 10.33005/jifti.v1i1.8.

[13] R. J. Putri, D. R. Saputri, M. Ifaya, H. Himaniarwati, M. P. Zulfikar, dan A. Nonovan, "Pemberian Informasi Obat Yang Tepat Kepada Masyarakat di Desa Puasana, Kecamatan Moramo Utara, Kabupaten Konawe Selatan," *J. Mandala Pengabdi. Masy.*, vol. 3, no. 2, hal. 196–201, 2022, doi: 10.35311/jmpm.v3i2.96.

[14] L. Irwanisyah *dkk.*, "Analisis Strategi Peningkatan Kepatuhan Pengobatan Pada Pasien Tuberkulosis Resisten Obat (Tbc-Ro) Di Indonesia," *J. Kesehat. Masy. Seroja*, vol. 4, no. 1, hal. 21–38, 2024.

[15] F. N. Darmawan, E. P. Silmina, dan T. Hardiani, "Sistem Klasifikasi Penyakit Kulit Menggunakan Metode Convolutional Neural Network (CNN) Berbasis Website," *Pros. Semin. Nas. Penelit. dan Pengabdi. Kpd. Masy.*, vol. 2, no. 2, hal. 871–881, 2024.

[16] D. A. Wijaya, A. Triayudi, dan A. Gunawan, "Penerapan Artificial Intelligence Untuk Klasifikasi Penyakit Kulit Dengan Metode Convolutional Neural Network Berbasis Web," *J. Comput. Syst. Informatics*, vol. 4, no. 3, hal. 685–692, 2023, doi: 10.47065/josyc.v4i3.3519.

[17] B. S. Nusantara dan M. Akbar, "Klasifikasi Penyakit Tuberculosis Berdasarkan Citra Rontgen Thorax Menggunakan Multi-Scale Convolutional Neural Network," *sudo J. Tek. Inform.*, vol. 3, no. 1, hal. 1–8, 2024, doi: 10.56211/sudo.v3i1.483.

[18] K. Anwar, R. Maruf, F. Susanto, dan M. B. Ryando, "Analisis Performa Deteksi Penyakit Paru-Paru dengan Model Klasifikasi Gambar Menggunakan LSTM Deep Learning," *J. Ilm. Univ. Batanghari Jambi*, vol. 25, no. 1, hal. 972, 2025, doi: 10.33087/jiubj.v25i1.5697.

[19] W. Widyawati, R. Sidik, E. Nuryani, dan P. Haryo Winasis, "Rancang Bangun Sistem Deteksi Katarak Menggunakan Metode Convolutional Neural Network," *J. Innov. Futur. Technol.*, vol. 7, no. 1, hal. 155–165, 2025, doi: 10.47080/iftech.v7i1.3895.

[20] W. Yosfand, K. U. Putra, dan A. Ramadhanu, "Berdasarkan Warna Dengan Median Filter, K-Means Pada Convolutional Neural Network," *J. Sci. Soc. Res.*, vol. 4307, no. 1, hal. 872–877, 2025, [Daring]. Tersedia pada: http://jurnal.goretanpena.com/index.php/JSSR

[21] R. Saputra, H. Erlanda, dan A. Ramadhanu, "Klasifikasi Citra Dalam Identifikasi Jeruk Nipis dan Jeruk Mandarin Menggunakan Convolutional Neural Network (CNN)," *JITSI J. Ilm. Teknol. Sist. Inf.*, vol. 5, no. 4, hal. 213–218, 2024, doi: 10.62527/jitsi.5.4.282.

[22] M. A. Djohar *dkk.*, "Liver Segmentation Using Convolutional Neural Network Method with U-Net Architecture," *J. Informatics Telecommun. Eng.*, vol. 6, no. 1, hal. 221–234, 2022, doi: 10.31289/jite.v6i1.6751.

Biographies of Authors

Dian Maharani, was born in Padang on January 29, 1991. He graduated with a Bachelor of Informatics Engineering (S1) at PLN Technical College, where he graduated in 2013. His primary and secondary education was taken at SD Pertiwi 3 Padang, SMP 25 Padang, SMA 4 Padang. Currently, he is continuing his studies at the Master's level (S2) with a major in Informatics Engineering at the Faculty of Computer Science, Universitas Putra Indonesia "YPTK" Padang, to further develop his expertise in the field of information technology and computing.

Prof. Dr. Yuhandi, S.Kom., M. Kom was born in Tanjung Alam on May 15, 1973. He is an assistant professor in Faculty of Computer Science, Universitas Putra Indonesia YPTK. He received the bachelor's degree in informatics management and master's degree in information technology in 1992 and 2006 from Universitas Putra Indonesia YPTK. Moreover, he completed his Doctor of Information Technology as informatics medical image expertise from Gunadarma University in April 2017. He is a lecturer at the Faculty of Computer Science, Universitas Putra Indonesia YPTK. He can be contacted at email: yuyu@upiyptk.ac.id.

	Dr. Jhon Veri, S.Kom., M.M., M.Kom., born in Kijang Island on July 8, 1971, is an academic and active researcher who adheres to Islam. He serves as Vice Rector IV at Putra Indonesia University "YPTK" Padang. He has NIDN 1008077101 and can be contacted via cellphone/WhatsApp number 08126629068. He is known as a figure who continues to strive for knowledge and provide the best contribution in his field, by making Imam Malik's quote as self-motivation: "It is not knowledge that should come to you, but you are the one who should come to that knowledge," as well as the principle of life: "It's an impossibility to be perfect, but it's possible to do the best.".