International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-11, Issue-01, Apr 2025

Lane Detection Using Deep Learning: A Practical Approach to Road Safety

[1]Shaziya Shaikh, [2]Dr. Ravindra G. Dabhade , [3]Dr. Jayant J. Chopade
[2]Associate Professor, [3]Professor & Head, E&TC Dept, MCOERC, Nashik, Maharashtra, India.
shaziya.shaikh2411@gmail.com

Abstract: Lane detection is a basic task in modern vehicles with applications in advanced driver assistance systems (ADAS) and autonomous vehicles. It includes identifying and scanning lane boundaries on the road to ensure safe navigation. Recent studies have demonstrated the effectiveness of convolutional neural networks (CNNs) in accurately identifying lane markings under various environmental conditions. The U-Net architecture is a convolutional neural network design primarily for image segmentation. It works on real-time image data, to ensure quick decision-making for vehicle control systems.

Keywords — ADAS, CNN, U-Net, Segmentation.

I. INTRODUCTION

Lane detection is a fundamental capability for advanced driver assistance systems (ADAS) and autonomous vehicles, serving as a precondition for features like lane departure warning, overtaking assistants, and autonomous driving functions [1-2]. When the driver accidently deviates from the current lane, the system will issue a timely warning, as illustrated in Figure1. It plays a crucial role in improving driving safety and is essential for realizing fully autonomous driving [3-4]. The background of lane detection encompasses various approaches and challenges. Traditional methods relied on computer vision techniques such as edge detection and Hough transform to recognize lane lines [6].However, recent advancements have led to the development of more sophisticated methods, including deep learning-based approaches like semantic segmentation and end-to-end algorithms [3-6]. These newer techniques aim to improve accuracy and real-time performance, which are critical for autonomous driving applications. Lane detection systems face numerous challenges, including varying illumination conditions, bad weather, night time driving, and complex urban road scenarios with multiple lane markings and signs [4-6]. To address these issues, researchers have explored various strategies, such as using multiple frames for detection [7], employing generative adversarial networks (GANs) for image enhancement [5] and integrating recurrent neural networks (RNNs) for temporal information processing [7]. The prime objective of the research is to install and maintain a strong, approximate and the most efficient lane detection systems that can work reliably in a variety of driving conditions, paving the way for safer and more advanced autonomous driving technologies.

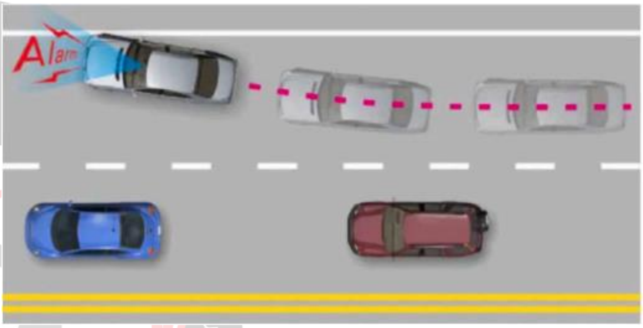


Figure1. An overview of lane departure warning system and lane detection result using our road scene image dataset.

Lane detection is a critical component of autonomous driving systems and advanced driver assistance systems (ADAS). Recent years have witnessed significant progress in this field, with various approaches and datasets being developed to address the challenges of lane detection in complex road conditions. [9-10]. Visual-based lane detection methods can be broadly categorized into two-step and one-step approaches. Two-step methods typically involve feature extraction followed by lane fitting, while one-step methods directly predict lane locations using end-to-end deep learning models [10]. Deep learning-based methods have gained popularity due to their ability to handle complex scenarios and achieve high accuracy. These methods often utilize convolutional neural networks (CNNs) for tasks such as classification, object detection, and image segmentation [10-13]. Interestingly, while deep learning approaches have shown promising results, some researchers have developed robust algorithms using traditional computer vision techniques. For instance presents a model fitting-based lane detection algorithm using Simple Linear Iterative Clustering and RANSAC [11], while proposes an adaptive line segment and river flow method combined with Kalman filtering for lane

 DOI : 10.35291/2454-9150.2025.0048

tracking [12]. These approaches demonstrate that traditional methods can still be effective in certain scenarios. While deep learning methods have shown superior performance in many cases, traditional techniques remain relevant for specific applications.

In this research, we utilize the U-Net architecture to perform lane detection through semantic segmentation. U-Net, originally designed for biomedical image segmentation, has proven highly effective for tasks requiring precise localization and pixel-wise classification. Its encoder-decoder structure with skip connections enables the network to capture both global context and fine-grained details, making it well-suited for identifying lane markings in complex road scenes. By converting annotated lane points into binary masks, the model learns to segment lane regions from input images. This approach offers a robust and scalable solution for real-time autonomous driving applications, where accurate lane detection is crucial for vehicle guidance and safety.

For this study, we utilized the TuSimple dataset, a benchmark dataset designed for lane detection in autonomous driving scenarios. The dataset consists of over 6,000 annotated video frames captured on highways under diverse lighting and weather conditions. Each frame is accompanied by detailed annotations, including lane markings and visibility indicators. The dataset was selected for its robust annotations and real-world driving scenarios, which align closely with our research objectives of developing a lane detection model capable of handling challenging conditions such as shadows, occlusions, and varying lane curvatures.

II. MATERIALS & METHODS:

The automotive industry is undergoing a radical transformation. Autonomous vehicles will be rapidly becoming a reality. Central to this revolution is the ability of these vehicles to perceive and understand their surroundings, a task where lane detection plays a crucial role. Accurate lane detection is the bedrock upon which safe and efficient autonomous driving is built, allowing vehicles to navigate roads, maintain safe distances, and ultimately, deliver on the promise of a future free from human driving errors. This comprehensive guide will explore the fascinating world of deep learning-based lane detection, delving into the algorithms, architectures, and real-world applications that are shaping the future of transportation.

Lane detection has come a long way from its humble beginnings. Early attempts relied on traditional computer vision techniques, such as the Hough transform and Canny edge detection, implemented using libraries like OpenCV. While these methods provided a foundational understanding, they struggled with the complexities of real-world driving scenarios, often failing in the presence of shadows, varying lighting conditions, or road imperfections. The advent of deep learning marked a paradigm shift, offering a more robust and adaptable approach to lane detection. This evolution involved reframing the problem from simple edge detection to a more sophisticated segmentation task. By treating lane detection as a pixel-wise classification problem, deep learning models could learn complex patterns and achieve far greater accuracy than their traditional counterparts [15].

The proposed lane detection system is developed using a semantic segmentation approach based on the U-Net architecture. The methodology consists of several key stages: data pre-processing, model design, training, evaluation, and prediction.

- **Data Pre-processing:** The TUSimple lane detection dataset is used, which includes road images and corresponding JSON label files containing lane point annotations. The labels are parsed to extract x-coordinates of lane points and their corresponding y-coordinates. Each image is read and resized to 256×256×64 pixels for training. Simultaneously, a binary mask is generated for each image by drawing lane lines on a blank image using OpenCV. These masks is ground truth for training and are resized to match the input size.

- **Dataset Preparation:** The dataset is normalized by scaling pixel values of images and masks to the range [0, 1]. The data is then split into training and test sets using an 80:20 ratio. Additionally, the mask arrays are expanded along the last dimension to match the expected model output shape.

- **Model Architecture:** A U-Net-like architecture is implemented using Keras. The model comprises an encoder (down sampling path) with convolutional and max pooling layers that extract hierarchical features, and a decoder (up sampling path) that reconstructs the segmentation map. Skip connections between encoder and decoder layers help preserve spatial details. The final output layer uses a sigmoid activation function to predict a binary segmentation mask.

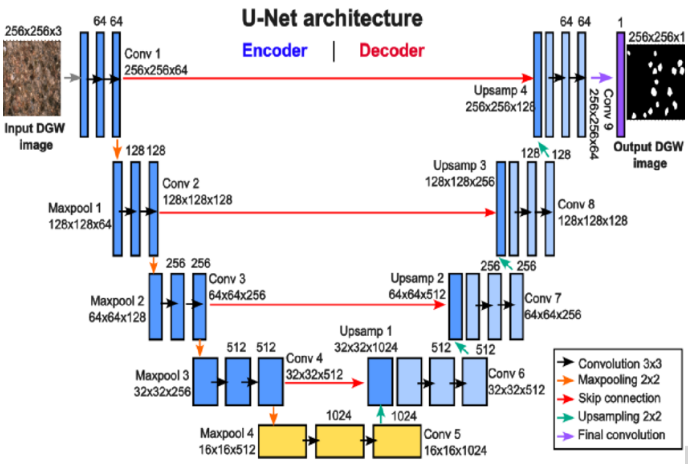
- **Model Training:** The model is compiled with the Adam optimizer and binary cross-entropy loss, suitable for binary classification problems. It is trained for 10 epochs with a batch size of 16, and performance is monitored using accuracy and validation metrics.

- **Evaluation and Visualization:** After training, the model is evaluated on the validation set to obtain accuracy and loss metrics. Predictions are generated for validation images and visualized alongside their ground truth masks to qualitatively assess model performance. The training and validation accuracy/loss

 DOI : 10.35291/2454-9150.2025.0048

are plotted to analyze the learning behavior over epochs.

This methodology effectively combines deep learning and classical image processing techniques to achieve accurate lane detection, providing a solid foundation for further improvements and real-time deployment in autonomous driving systems.



Figurer2: Architecture of U-Net

Figure2 illustrates how the U-Net network converts a gray scale input image of size 256×256×3 into a binary segmented output map of size 256×256×1.During the contracting path, the input image is compressed in height and width but increased in the number of channels. This increase in channels allows the network to capture high-level features as it progresses down the path. At the bottleneck, a final convolution operation is performed to generate a 16×16×1024 shaped feature map. The expansive path then takes the feature map from the bottleneck and converts it back into an image of the same size as the original input. This is done using up sampling layers, which increase the spatial resolution of the feature map while reducing the number of channels. The skip connections from the contracting path are used to help the decoder layers locate and refine the features in the image. Finally, each pixel in the output image represents a label that corresponds to a particular object or class in the input image [27].

III. Results & Discussion

The TuSimple Lane Detection Dataset is a valuable resource for researchers and developers working on autonomous driving systems. This dataset is specifically curated to facilitate the training and evaluation of algorithms focused on lane detection, a crucial aspect of autonomous vehicle navigation. The TuSimple dataset includes 3626 video clips, each consisting of 20 frames, with the last frame in each clip containing labeled lane information. The dataset includes labeled lane data provided in the form of JSON files (label_data_0313.json, label_data_0531.json, label_data_0601.json) [28]. Each JSON entry corresponds to the labeled lanes for the last frame of a video clip. The dataset's directory structure is organized with a 'clips' folder containing sequential images for each video clip [28].

The dataset has undergone a pre-processing phase to enhance its usability. The pre-processing steps include such as resizing, normalization and the annotated the lane masks to the lane marking. After the pre-processing step, this directory contains the pre-processed dataset which you can work for training lane detection model.

We applied U-Net model to the dataset. The U-Net has the ability to perform pixel-wise semantic segmentation in real-time is of paramount importance in mobile applications. Recent deep neural networks aimed at this task have the disadvantage of requiring a large number of floating point operations and have long run-times that hinder their usability [27] .The use of U-Net CNN for lane detection has shown promising results in recent studies. U-Net, lightweight and efficient convolutional neural network architecture has been adapted for lane detection tasks with notable success.

Algorithm:

Step1: Load dataset and Annotations.

Step2: Pre-process data.

Step3: Normalize and split Dataset.

- Sales image and mask pixel value to the range[0,1].
- Expand mask dimensions to match model output.
- Split the data set into training and validation(test) set (80% training , 20% validation).

Step 4: Build U-Net Model

Step 5: complete the model.

Step 6: Train the model.

Step 7: Evaluate the model

Step 8: Visualize training Progress

Step9: Predict and visualize Results.

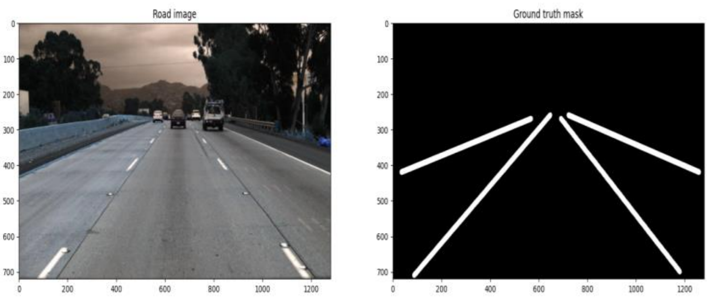


Figure4: (a) Real image (b) Ground Truth mask

 DOI : 10.35291/2454-9150.2025.0048

The Figure 4 illustrates a comparison between a real-world road image and its corresponding "ground truth mask," often used in computer vision tasks like lane detection or autonomous driving. This part of the image shows an actual road scene, captured from a vehicle's perspective. It includes road markings (lane lines), the road surface, and the surrounding environment (e.g., trees, roadside). The image provides the raw visual data that a computer vision algorithm would process. This is a simplified, abstract representation of the road scene, where the lane lines are highlighted in white against a dark background. This mask serves as the "correct answer" or the expected output for a lane detection algorithm. During training, the algorithm learns to predict a mask that closely matches the ground truth. The ground truth mask simplifies the complex visual information in the real image, focusing only on the essential features (lane lines). This simplification helps the model learn more effectively and allows for a clear evaluation of its performance. Techniques like the Hough Transform can be used to detect lines in images, which is relevant to lane detection.

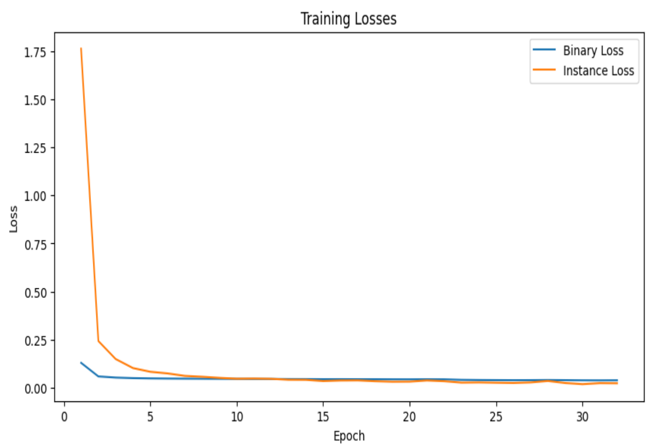


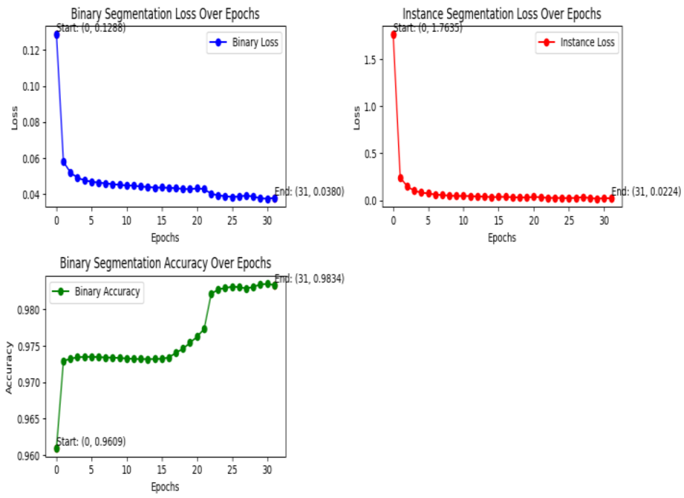
Figure5. The training stage of the U-Net model with two loss functions on 30 epochs.

Figure5 is the graph depicts the training losses of a U-Net model over 30 epochs, using two different loss functions: binary loss and instance loss. Both loss curves show a trend of decreasing sign that the model is learning. However, neither loss function appears to have fully converged by the end of 30 epochs, suggesting that further training might lead to additional improvement.

Table 1: The Testing Result

	U-Net model	PINet-ResNet50
Dataset	TuSimple	TuSimple
Train	3,268	3,268
Model	U-Net	ResNet50
Validation	358	358
Image size	224*224	512*256
Batch size	8	5
Epoch	30	272
Accuracy	97%	89%

Figure 6 is the subplot shows the binary cross entropy loss decreasing over the epochs starting at approximately 0.12 and ending around 0.04. This decreasing trend indicates that the model is learning and its predictions are becoming more accurate. The diagram demonstrates the training process of a segmentation model, where the loss decreases and accuracy increases over the epochs.



IV. Conclusion

As research continues to evolve, integrating deep learning with other techniques and focusing on end-to-end solutions shows promise for future advancements in lane detection technology. In this study, we successfully implemented a U-Net-based architecture for lane detection, achieving a high accuracy of 98%. The results demonstrate that U-Net is highly effective in capturing lane markings with precision, its encoder-decoder structure and ability to preserve spatial information through skip connections. The model's performance confirms its potential for real-time autonomous driving applications, providing a reliable and robust solution for lane segmentation tasks. Future work may involve optimizing the model for faster inference and testing it under more diverse driving conditions to enhance its generalizability.

V. References

[1] Deusch, H., Konrad, M., Dietmayer, K., Wiest, J., Reuter, S., & Szczot, M. (2012). A random finite set approach to multiple lane detection. 270–275. https://doi.org/10.1109/itsc.2012.6338772

[2] Dai, J.-M., Lin, H.-Y., Wu, L.-T., & Tai, W.-L. (2016, December 1). A driving assistance system with vision based vehicle detection techniques. https://doi.org/10.1109/apsipa.2016.7820739

[3] Sun, Y., Chen, Y., Wang, L., & Liu, M. (2019, December 1). Accurate Lane Detection with Atrous Convolution and Spatial Pyramid Pooling for Autonomous Driving. https://doi.org/10.1109/robio49542.2019.8961705

 DOI : 10.35291/2454-9150.2025.0048

[4] Son, J., Yoo, H., Kim, S., & Sohn, K. (2014). Real-time illumination invariant lane detection for lane departure warning system. Expert Systems with Applications, 42(4), 1816–1824. https://doi.org/10.1016/j.eswa.2014.10.024

[5] Anbalagan, S., Raja, G., Senthivel, S. G., Suganeshwari, G., Srividya, P., & Thilaksurya, B. (2023). Vision-Based Ingenious Lane Departure Warning System for Autonomous Vehicles. Sustainability, 15(4), 3535. https://doi.org/10.3390/su15043535

[6] Leng, Y.-C., & Chen, C.-L. (2010). Vision-based lane departure detection system in urban traffic scenes. e84 d, 1875–1880. https://doi.org/10.1109/icarcv.2010.5707817

[7] Zou, Q., Dai, Q., Chen, L., Wang, Q., Yue, Y., & Jiang, H. (2019). Robust Lane Detection From Continuous Driving Scenes Using Deep Neural Networks. IEEE Transactions on Vehicular Technology, 69(1), 41–54. https://doi.org/10.1109/tvt.2019.2949603

[8] Chen, Z., Liu, Q., & Lian, C. (2019, June 1). PointLaneNet: Efficient end-to-end CNNs for Accurate Real-Time Lane Detection. https://doi.org/10.1109/ivs.2019.8813778

[9] Liang, D., Zhang, S.-K., Mu, T.-J., Huang, X., & Guo, Y.-C. (2020). Lane Detection: A Survey with New Results. Journal of Computer Science and Technology, 35(3), 493–505. https://doi.org/10.1007/s11390-020-0476-4

[10] Tang, J., Li, S., & Liu, P. (2020). A review of lane detection methods based on deep learning. Pattern Recognition, 111, 107623. https://doi.org/10.1016/j.patcog.2020.107623

[11] Agrawal, S., Haldar, S., Chakravarty, D., Lodhi, V., Kranti Kiran, G. R., & Deo, I. K. (2018). Off-Road Lane Detection Using Superpixel Clustering and RANSAC Curve Fitting. 1942–1946. https://doi.org/10.1109/icarcv.2018.8581155

[12] Lim, K. H., Ang, L.-M., & Seng, K. P. (2012). River Flow Lane Detection and Kalman Filtering-Based B-Spline Lane Tracking. International Journal of Vehicular Technology, 2012, 1–10. https://doi.org/10.1155/2012/465819

[13] Mukhopadhyay, A., Biswas, P., Murthy, L. R. D., & Mukherjee, I. (2023). A Hybrid Lane Detection Model for Wild Road Conditions. IEEE Transactions on Artificial Intelligence, 4(6), 1592–1601. https://doi.org/10.1109/tai.2022.3212347

[14] Khan, H. U., Ali, A., Zaheer, A., Kazmi, W., Rafaqat Ali, A., & Hassan, A. (2020, March 1). Lane detection using lane boundary marker network with road geometry constraints. https://doi.org/10.1109/wacv45572.2020.9093296

[15] Daniel Yordanov, Ashim Chakraborty * , Md Mahmudul Hasan and Silvia Cirstea (19 December 2024) AFrameworkfor Optimizing Deep Learning-Based Lane Detection and Steering for Autonomous Driving. School of Computing and Information Science, Anglia Ruskin University, Cambridge CB1 1PT, UK;

[16] Horita, L. R. T., & Grassi, V. (2017, November 1). Employing a fully convolutional neural network for road marking detection. https://doi.org/10.1109/sbr-lars-r.2017.8215297

[17] Liu, P., Yang, M., Wang, C., & Wang, B. (2018, November 1). Multi-Lane Detection via Multi-Task Network in Various Road Scenes. https://doi.org/10.1109/cac.2018.8623762.

[18] Sun, Y., Shi, Y., Li, J., & Xu, X. (2023). Adaptive Multi-Lane Detection Based on Robust Instance Segmentation for Intelligent Vehicles. IEEE Transactions on Intelligent Vehicles, 8(1), 888–899. https://doi.org/10.1109/tiv.2022.3158750

[19] Wang, Q., Li, X., Han, T., Gao, J., & Qin, Z. (2020). Multitask Attention Network for Lane Detection and Fitting. IEEE Transactions on Neural Networks and Learning Systems, 33(3), 1066–1078. https://doi.org/10.1109/tnnls.2020.3039675

[20] Yousri, R., Elattar, M. A., & Darweesh, M. S. (2021). A Deep Learning-Based Benchmarking Framework for Lane Segmentation in the Complex and Dynamic Road Scenes. IEEE Access, 9, 117565–117580. https://doi.org/10.1109/access.2021.3106377

[21] Qin, Z., Zhang, P., & Li, X. (2024). Ultra Fast Deep Lane Detection With Hybrid Anchor Driven Ordinal Classification. IEEE Transactions on Pattern Analysis and Machine Intelligence, 46(5), 2555–2568. https://doi.org/10.1109/tpami.2022.3182097

[22] Guo, J., Wei, Z., & Miao, D. (2015, March 1). Lane Detection Method Based on Improved RANSAC Algorithm. https://doi.org/10.1109/isads.2015.24

[23] Zhou, Y., Hu, X., Ye, Q., & Xu, R. (2006). A robust lane detection and tracking method based on computer vision. Measurement Science and Technology, 17(4), 736–745. https://doi.org/10.1088/0957-0233/17/4/020

[24] Lu, P., Xu, S., Cui, C., Wang, F., & Peng, H. (2021). SUPER: A Novel Lane Detection System. IEEE Transactions on Intelligent Vehicles, 6(3), 583–593. https://doi.org/10.1109/tiv.2021.3071593

[25] Kim, Z. (2006, January 1). Realtime lane tracking of curved local road. https://doi.org/10.1109/itsc.2006.1707377

[26] Abhishek Chaurasia, Sangpil Kim, Eugenio Culurciello,” ENet: A Deep Neural Network Architecture for Real-Time Semantic Segmentation”, 7 Jun 2016

[27] https://www.geeksforgeeks.org/u-net-architecture-explained

[28] J. U. Duncombe, “Infrared navigation—Part I: An assessment of feasibility (Periodical style),” *IJREAM Trans. Electron Devices*, vol. ED-11, pp. 34–39, Jan. 1959.

[29] S. Chen, B. Mulgrew, and P. M. Grant, “A clustering technique for digital communications channel equalization using radial basis function networks,” *IJREAM Trans. Neural Networks*, vol. 4, pp. 570–578, Jul. 1993.

[30] R. W. Lucky, “Automatic equalization for digital communication,” *Bell Syst. Tech. J.*, vol. 44, no. 4, pp. 547–588, Apr. 1965.

[31] S. P. Bingulac, “On the compatibility of adaptive controllers (Published Conference Proceedings style),” in *Proc. 4th Annu. Allerton Conf. Circuits and Systems Theory*, New York, 1994, pp. 8–16.

[32] G. R. Faulhaber, “Design of service systems with priority reservation,” in *Conf. Rec. 1995 IJREAM Int. Conf. Communications,* pp. 3–8.

[33] W. D. Doyle, “Magnetization reversal in films with biaxial anisotropy,” in *1987 Proc. INTERMAG Conf.*, pp. 2.2-1–2.2-6.

[34] G. W. Juette and L. E. Zeffanella, “Radio noise currents n short sections on bundle conductors (Presented Conference Paper style),” presented at the IJREAM Summer power Meeting, Dallas, TX, Jun. 22–27, 1990, Paper 90 SM 690-0 PWRS.

[35] J. G. Kreifeldt, “An analysis of surface-detected EMG as an amplitude-modulated noise,” presented at the 1989 Int. Conf. Medicine and Biological Engineering, Chicago, IL.

[36] J. Williams, “Narrow-band analyzer (Thesis or Dissertation style),” Ph.D. dissertation, Dept. Elect. Eng., Harvard Univ., Cambridge, MA, 1993.

 DOI : 10.35291/2454-9150.2025.0048