

HUMAN DETECTION WITH PLANT BIOELECTRIC SIGNAL
Haitsam¹, Abdur Rabi'², Rahman Ariffudin³
Fakultas Teknik, Universitas Merdeka Malang
Jalan Terusan Dieng. 62-64 Klojen, Pisang Candi, Sukun, Kota Malang
email: haitsam26@gmail.com
email: arrabik@unmer.ac.id
email: rahman.arifuddin@unmer.ac.id

ABSTRACT

This research aims to utilize the bioelectric potential of plants as a tool to detect human presence in the surrounding area. The potential bioelectric signals of plants are recorded using a data logger and analyzed with the help of a computer for identification. Previous methods used time series models and Z-value tests, but challenges in achieving accurate estimates remain. We use Recurrent Neural Networks (RNN) to handle the processing of large datasets in this study. The experimental results show that the RNN model is very effective and achieves a high level of accuracy, with a perfect accuracy of 1.00 from the total duration of each class is 62030 seconds (379610 samples). 303688 data samples are used as train datasets, while the others (75922 samples) are used as validation datasets. This shows that RNN has great potential in processing plant bioelectric data to detect human presence with very high accuracy.

Kata kunci: Bioelectric Potential Of Plants, RNN, ROC

INTRODUCTION

Bioelectric is a field of study that delves into the electrical potential in human body organs, encompassing electrical and magnetic phenomena, and the utilization of electricity and magnetism on the body's surface. Additionally, bioelectric also explores the living electrical power in plants, particularly in leaves. Using plants as sensors for monitoring or detecting humans is an interesting research topic. In some countries like Japan, elderly people may feel uncomfortable with the numerous constantly active surveillance devices. Plant-based biological sensors can optimize bioelectric potential to detect human presence unobtrusively. This bioelectric signal will be recorded using a data logger and then processed using a computer.

Previous research used a manual decision-making method with the multi-objective particle swarm optimization algorithm for solving a numerical association rule mining problem (MOPAR). This method was executed using Matlab and involved two plants at different distances. The research results show that MOPAR performs quite well, with human location estimation from three different positions achieving an average accuracy of 75%. (Tahyudin and Nambo, n.d.)

The second research is by Choiri Muchlis, Universitas Merdeka Malang, 2023, titled "Implementation and Analysis of Plant Bioelectric Potential Data Logger to Detect Human Presence." In this study, the z-test method was used. The data in this research was collected with a sampling interval of 20 ms (50S/s). The selection of this interval is expected to improve the accuracy of data analysis. The data collection time in this study was set to 5 minutes. The research provided fairly accurate results, but the method used was considered less complex. (Muchlis, Rabi', and Sumarahinsih, n.d.)

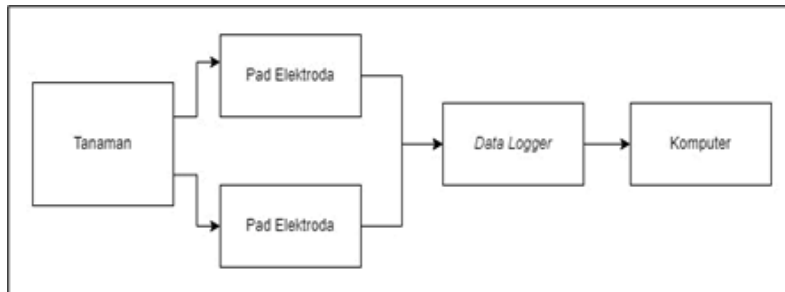
This research uses recurrent neural networks (RNN), powerful tools for prediction and sequence analysis, enabling advancements in various fields that require understanding and generating sequential data. By addressing challenges such as vanishing gradients and integrating advanced architectures like long short-term memory recurrent neural network (LSTM-RNN) (IBM, n.d.; Bai, Kolter, and Koltun 2018) and GRU, RNN continues to be a fundamental component of modern machine learning and artificial intelligence applications.

RESEARCH METHODS

This research uses a Deep Learning approach by utilizing a model (RNN). The selection of this method aims to detect bioelectric signals originating from plants, to determine whether the obtained signals indicate the presence of humans.

System Block Diagram

The system block diagram illustrates the structure for planning the collection of bioelectric potential data from plants. Electrode pads are used as sensors to record and log bioelectric signals by the data logger.

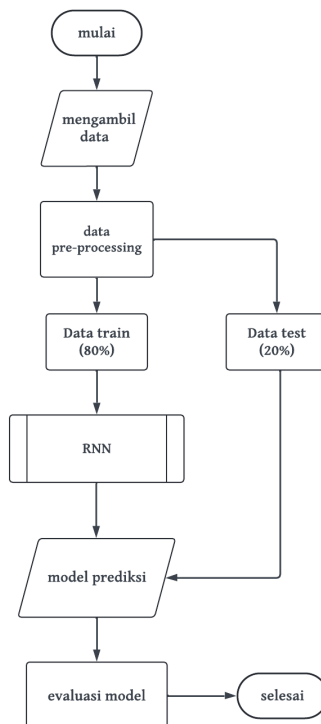


Gambar 1. Data Collection Process Diagram

The block diagram illustrates the data acquisition stage from the plant to the data logger, facilitated by connecting the data logger and computer. An electrode pad is attached to a leaf and connected via a cable. Utilizing a computer makes data collection more efficient and easier to manage.

Flowchart

A flowchart is a visual illustration of an algorithm applied in a program. A flowchart is a diagram that details the workflow of a system and illustrates the stages within that system.



Gambar 2. Programming Flow Diagram

This flowchart illustrates developing a prediction model using a Recurrent Neural Network (RNN), starting with data collection from relevant sources, followed by a pre-processing stage to prepare the data. After that, the data is divided into two parts: 80% is used to train the model (training data) and 20% to test the model (testing data). The RNN model is then trained using the training data to predict the output based on the given input. After the model is trained, predictions are made on the testing data, and these predictions are evaluated to assess the model's performance using accuracy evaluation metrics. This process ends with the model evaluation stage, after which the process is considered complete.

Recurrent Neural Network (RNN)

Recurrent neural network (RNN) is a type of artificial neural network that uses sequential data or time series data. This deep learning algorithm is generally used for ordinal or temporal problems, such as language translation, Natural Language Processing (NLP), speech recognition, and image captioning; they are also integrated into popular applications like Siri, voice search, and Google Translate. Like feedforward neural networks and Convolutional Neural Networks (CNN) (Sari et al. 2022), recurrent neural networks leverage training data to learn. They are distinguished by their "memory" because they take information from previous inputs to influence the current input and output. While traditional neural networks assume that inputs and outputs are independent of each other, the output of recurrent neural networks depends on previous elements in the sequence. Although future events will also help determine the output of a given sequence, unidirectional recurrent neural networks cannot consider these events in their predictions. RNN processes input and processes it with previously obtained information, so the decision or outcome of an input is influenced by the existing information system because RNN has an internal memory that can remember a set of information.

RESULTS AND DISCUSSION

Data Collection

In this study, the plant used is *Epipremnum Aureum*, commonly known as golden pothos. This plant was chosen because it is an indoor plant with an extraordinary ability to survive in closed-room conditions. In addition to its ability to survive in environments with limited lighting and air circulation, *Epipremnum Aureum* is also known for its capability to detect changes in its surroundings through bioelectric signals, making it an ideal subject for this research.

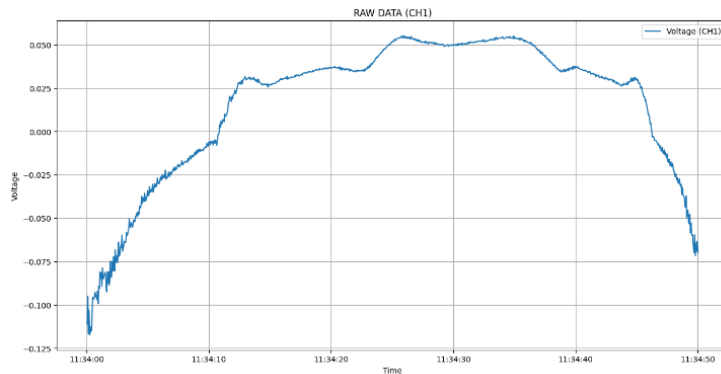


Gambar 3. Data Collection Process

Data collection was conducted in an enclosed room with stable temperature and lighting. The electrode pads are attached to the leaves of the plants facing the access road inside the room, with the distance between humans and the plants set between 1-2 meters. This arrangement is made to maximize the recording of bioelectric signals by the data logger and minimize signal interference or noise. The controlled room

conditions and strategic placement of the electrodes aim to ensure that changes in electrical potential on the leaves can be detected more accurately, resulting in data that is more precise and free from external disturbances.

The data recorded by the data logger is stored in CSV (comma-separated values) format (Liu Xiaoze, n.d.), which is a data format where each recorded data point is separated by a comma (,) or semicolon (;). This CSV format greatly facilitates data storage and processing.

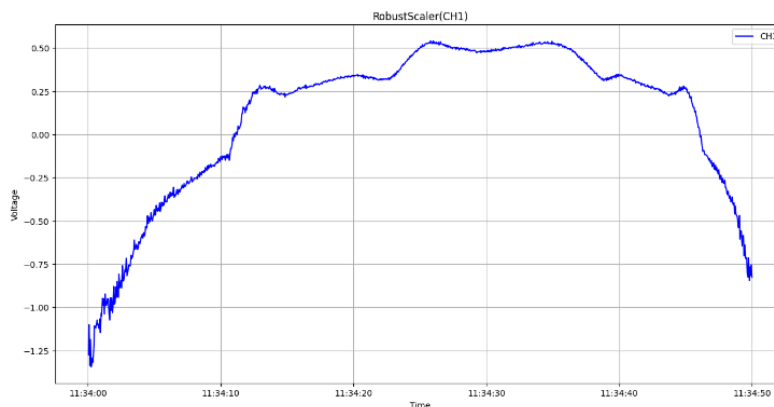


Gambar 4. Raw Data Plot

The data recorded by the data logger is then plotted. In this study, the data is collected with a sampling interval of 20 ms. (50 sampel per detik). The collected data is stored in CSV format to facilitate further analysis. The plot of this data provides a clear visualization of the patterns and variations of the bioelectric signals generated by the plants during the observation period, aiding in the identification and detection of human presence around the plants.

Signal Normalization

Signal normalization is the process of converting a signal into a normal form to facilitate further analysis or processing. To eliminate scale differences between various signals to facilitate comparison and analysis. This can also help reduce distortion or interference that may occur in the signal, improve signal quality, and enhance the efficiency of data processing and interpretation. With normalization, the information contained in the signal becomes easier to understand and extract.



Gambar 5. RobustScaler

The signal is normalized using RobustScaler. RobustScaler is a normalization method that is resistant to outliers in the data. It uses a stronger estimate to ensure that outlier values do not significantly affect the normalization.(proclusacademy, n.d.). This method subtracts the median and then divides it by the interquartile range of each feature, making it better at handling data with outliers. With the formula:

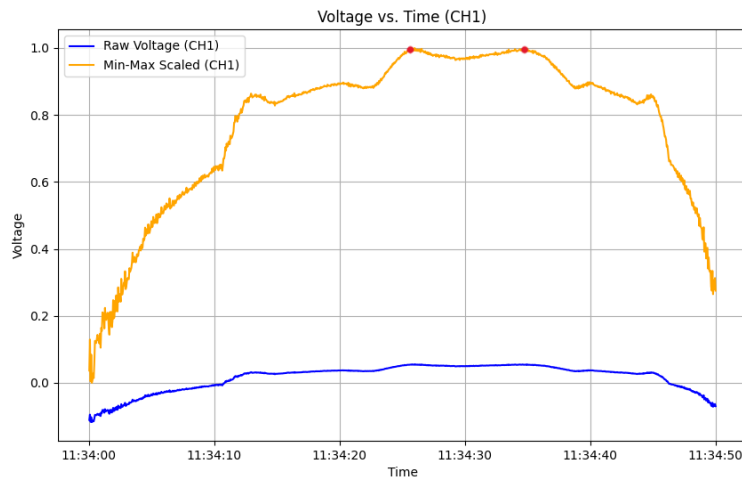
$$X_{scaled} = \frac{X - \text{median}(X)}{IQR(X)} \quad (1)$$

Xscaled : normalized value

X : original value

Median (X) : median value of the data

IQR(X) : interquartile range of the data



Gambar 6. RobustScaler

Meanwhile, MinMaxScaler is a normalization method that transforms data into a certain range, usually between 0 and 1. This is done by subtracting the minimum value from each data point and then dividing it by the difference between the maximum and minimum values of the obtained data. With the formula:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

Xscaled : normalized value

X : original value

Xmin : minimum value of the data

Xmax : maximum value of the data

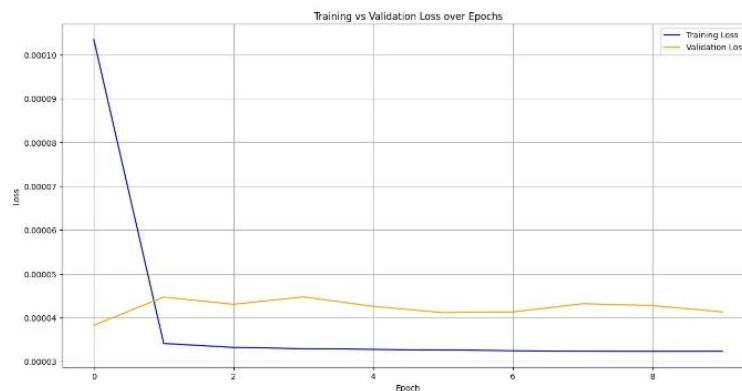
By applying normalization using these two methods, signals that previously had different scales or distributions, as well as a wide range of values, can be adjusted into a uniform and controlled scale. This helps in improving the ability to analyze or process signals more consistently and accurately, as well as reducing the likelihood of being affected by noise or disturbances that may be present in the original data.

Thus, normalizing signals using the RobustScaler and MinMaxScaler methods plays a crucial role in enhancing the quality and reliability of the data to be used in further analysis or processing. (geeksforgEEKS, n.d.).

Data Validation

Validation loss is a metric used to assess the performance of a deep learning model on the validation set (SkillPlus, n.d.; Baeldung, n.d.). The validation set is a portion of the dataset set aside to validate the model's performance. Validation loss is similar to training loss and is calculated from the number of errors for each example in the validation set. Additionally, validation loss is measured after each training period, providing information on whether the model requires further tuning or adjustment. This is done by plotting the learning curve for validation loss.

During the data validation stage, the training process was carried out with 10 epochs, using a batch size of 32, and the Adam optimizer with a learning rate of 0.001. The total duration of each class is 62030 seconds. (379610 Sampel). 303,688 data samples were used as the training dataset, while the remaining 75,922 samples were used as the validation dataset. This stage is important to evaluate how well the model can generalize to data it has never seen before, ensuring its effectiveness beyond the training set.



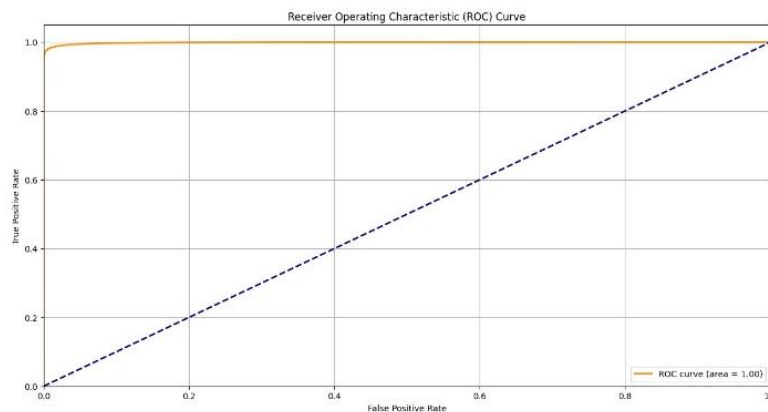
Gambar 7. Training vs Validation loss

Training Loss initially was higher, then significantly decreased and stabilized below validation loss, indicating that the model is undergoing an effective training process and has successfully overcome some initial challenges. At the beginning of the training, the high training loss was caused by initial randomness, random parameter initialization, or early instability in the optimization process. If the training loss decreases significantly and stabilizes below the validation loss, this indicates that the model has converged, meaning it has successfully "learned" patterns in the training data and can make good predictions on new data. If the validation loss is also low, this shows that the model is capable of generalizing well to data that was not seen during training, indicating that the model is not just "memorizing" the training data but can also handle new data. Furthermore, if the training loss remains low and stable, and there are no signs of an increase in validation loss, this is a good indication that the model is not experiencing overfitting, meaning the model is not too complex and can generalize well to new data.

Evaluation Model

Several metrics and techniques can be used in model evaluation, in this study using Receiver Operating Characteristic (ROC) to evaluate model performance. The Receiver Operating Characteristic (ROC) function is an important tool in evaluating the performance of classification models by visualizing the levels of sensitivity and specificity at various class separation thresholds. (evidentlyai.com, n.d.; skicitlearn, n.d.). ROC allows for direct comparison between several classification models based on the area under the ROC curve (AUC), where a higher AUC value indicates better performance. Additionally, ROC enables the

determination of optimal thresholds that align with application needs and demonstrates resistance to class imbalance in the dataset. Thus, ROC provides valuable insights for practitioners in selecting the best model and making the right decisions in various classification contexts.



Gambar 8. ROC

ROC curve area = 1.00, which indicates that the model has perfect performance in distinguishing between positive and negative classes. This means that the model can separate positive and negative instances without any errors. This is a highly desirable outcome and rarely occurs in practice.

CONCLUSION

This study on the use of the RNN model to identify the presence of humans around plants can proceed well. Validation results show that the validation loss remains stable above the training loss, indicating that the model successfully "learned" patterns in the training data and can provide good predictions on new data. In the AUC-ROC evaluation process, a value of 1.00 was achieved, which is a perfect result indicating that the RNN model used completed the task with a good level of accuracy, from the data preprocessing stage to the final results. With some adjustments, this model can operate effectively and demonstrate its best performance on the tested dataset. Nevertheless, there is still potential to further improve this experiment in the future.

REFERENCE

- [1] Baeldung. n.d. "Training and Validation Loss in Deep Learning." Accessed May 30, 2024. <https://www.baeldung.com/cs/training-validation-loss-deep-learning>.
- [2] Bai, Shaojie, J. Zico Kolter, and Vladlen Koltun. 2018. "An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling," March. <http://arxiv.org/abs/1803.01271>.
- [3] evidentlyai.com. n.d. "How to Explain the ROC Curve and ROC AUC Score?" Accessed June 13, 2024. <https://www.evidentlyai.com/classification-metrics/explain-roc-curve>.
- [4] geeksforgeeks. n.d. "Teknik StandardScaler, MinMaxScaler Dan RobustScaler – ML." Accessed June 2, 2024. <https://www.geeksforgeeks.org/standardscaler-minmaxscaler-and-robustscaler-techniques-ml/>.

- [5] IBM. n.d. "What Are Recurrent Neural Networks?" Accessed May 20, 2024. <https://www.ibm.com/topics/recurrent-neural-networks>.
- [6] Liu Xiaoze. n.d. "Study on the Application of Bioelectric Potential of Living Plants." Accessed June 7, 2024. [file:///C:/Users/USER/AppData/Local/Microsoft/Windows/INetCache/IE/N450H0VZ/poster\[1\].pdf](file:///C:/Users/USER/AppData/Local/Microsoft/Windows/INetCache/IE/N450H0VZ/poster[1].pdf).
- [7] Muchlis, Choiri, Abd Rabi', and Andrijani Sumarahinsih. n.d. "SNESTIK Seminar Nasional Teknik Elektro, Sistem Informasi, Dan Teknik Informatika Implementasi Dan Analisis Data Logger Potensi Biolistrik Tumbuhan Untuk Mendeteksi Keberadaan Manusia." <https://doi.org/10.31284/p.snestik.2023.4220>.
- [8] proclusacademy. n.d. "Robust Scaling: Why and How to Use It to Handle Outliers." Accessed May 31, 2024. <https://proclusacademy.com/blog/robust-scaler-outliers/>.
- [9] Sari, Angraini Puspita, Hiroshi Suzuki, Takahiro Kitajima, Takashi Yasuno, Dwi Arman Prasetya, and Rahman Arifuddin. 2022. "Short-Term Wind Speed and Direction Forecasting by 3DCNN and Deep Convolutional LSTM." *IEEJ Transactions on Electrical and Electronic Engineering* 17 (11): 1620–28. <https://doi.org/10.1002/tee.23669>.
- [10] skicit learn. n.d. "Receiver Operating Characteristic (ROC) with Cross Validation." Accessed May 23, 2024. https://scikit-learn.org/stable/auto_examples/model_selection/plot_roc_crossval.
- [11] SkillPlus. n.d. "Data Training, Validation Dan Test." Accessed May 30, 2024. <https://www.baeldung.com/cs/training-validation-loss-deep-learning>.
- [12] Tahyudin, Imam, and Hidetaka Nambo. n.d. "Estimating Position of Bio Electric Potential Dataset as A Natural Sensor Using Time Series Approach."
- [13] Oezkaya, B., & Gloor, P. A. *Recognizing Individuals and Their Emotions Using Plants as Bio-Sensors through Electro-static Discharge*. arXiv preprint arXiv:2005.04591, 2020.
- [14] Zhang, D., & Zhang, Y. *Deep learning algorithm for room temperature detection using plant bioelectric signals*. *Biosystems Engineering*, 225, 1-10, 2024.
- [15] Kobayashi, H., & Suzuki, M. *Bioelectric potentials of plant for determining human positions*. *Sensors and Materials*, 30(7), 1507-1516, 2018.