Implementation of Neural Network Control for Foot Prosthesis as Foot Function Reconstruction in Post-Amputation Patients

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***Abstract*—The purpose of this paper is to show the robot's bionic legs can be moved automatically by applying a deep learning neural network as a control system to improve the function of the bionic legs. The deep learning neural network control system resembles the nerve network in the legs, so it requires a dataset of thigh muscle strength variations, and knee joint angles during the process of walking, going up and down stairs. This dataset is used in the design using the Recurrent Neural Network-Long Short-Term Memory (RNN-LSTM) model through a training process so that an optimal model is obtained using the Tensor flow API to be implemented into the prosthetic leg system. Deep learning control systems require a lot of data for model training, so this study uses a combination of sensors, namely the FSR402 sensor and the MPU sensor. By using a control system based on RNN-LSTM the performance of the robot's leg movements is better and has a very small error.**

***Keywords*—prosthesis leg robot, neural network, deep learning, Recurrent Neural Network Long Short-term Memory (RNN-LSTM)**

I. INTRODUCTION

There are 15 out of 100 people in the world who experience disabilities, namely the condition of individuals who are unable to carry out an activity normally due to loss of bodily functions, both psychologically, physiologically, and anatomically [1]. Obstacles in the form of loss of function of body parts will cause difficulty in carrying out normal activities. Daily activities that require a lot of movement will certainly make it difficult for persons with disabilities in body parts that play a large role in mobility, such as limbs. This will certainly hamper social activities that people with disabilities want to carry out [2]. What's more, the limbs, especially the feet, play an important role in most human activities [3]. Not a few people with disabilities are patients who have gone through the leg amputation process due to injuries from major accidents. A study conducted by [4] even shows that one of the areas that have a high amputation rate is Southeast Asia.

Post-amputated patients must adjust their physical limitations in activities. This can affect the psychological condition of the patient, especially for patients with major trauma and who have not been able to fully accept themselves as a person with a disability. According to studies that have been conducted, the level of depression found in post-amputation patients varies from 20.6% to 63%, while anxiety is found to range from 25.45% to 57% [5]. Intervention in psychological conditions in post-amputation patients is very important to implement. Socially, of course, a surrounding environment is needed that is able to support the recovery of the psychological conditions of patients after arm and hand amputations. Efforts to restore arm function can also be a solution so that post-amputation patients can return to a complete body condition.

As a solution to improve the quality of life for post-amputation patients, the development of restoration of upper limb function in the form of foot prostheses continues to develop. Early in its development, a mechanical prosthesis was constructed to restore the function of the leg as a static prosthesis. However, this kind of foot prosthesis requires more manual control and makes the user feel relatively uncomfortable. This condition causes high rejection of mechanical prostheses in society [6]. Therefore, the development of the ergonomic aspects of the foot prosthesis was also carried out. One of the ergonomic updates that have been studied by [7] states that the aspect of pressure and the suitability of the size (fitting) of the socket to attach the prosthesis to the remaining leg greatly influences user comfort.

The functional aspects of the foot prosthesis also need to be reviewed and considered in more detail. Various studies related to the development of automatic control of robot legs have been carried out. Most studies pay more attention to the use of Electromyography (EMG) and Electroencephalography (EEG) sensors [8]. However, the mechanism of these two sensors is practically still

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fluctuating and cannot represent input properly due to different human physical conditions. Therefore, the use of appropriate sensors and the availability of certain work algorithms in the design and construction of arm prostheses are very necessary. These approaches are intended so that the movement produced by the arm prosthesis is able to represent its original condition.

Referring to these problems, it is necessary to increase the functionality of the control system and design aspects. Therefore, this research was designed to build a prosthesis foot product by using a deep-learning neural network as a control system to improve the functionality of the bionic leg. The deep learning neural network control system resembles the nerve network in the legs, so it requires a dataset of variations in the strength of the thigh muscles, and the angles of the knee joints during the process of walking, going up and down stairs. The rest of this dataset will be used to design and compare a deep learning neural network model using an RNN-LSTM through a training process so that an optimal model is obtained using the Tensor flow API for implementation. -deploys to the bionic leg system. Deep learning control systems require a lot of data for model training, so this study uses a combination of sensors, namely the FSR402 sensor and the MPU sensor. The FSR402 sensor is used because it is responsive to the surface of the leg muscles [9]. The combination of sensors will produce a good performance in producing foot movements according to the gait cycle. The trained model can predict the output (knee angle) so that the bionic leg movements are more adaptive and follow the gait cycle. Through this research, it is hoped that bionic foot products will be obtained that are safer and adaptive according to the walking cycle.

II. Research Methods

A. Research Design

This research was carried out to develop a bionic leg design integrated with a deep learning neural network control system, in which the bionic leg uses conventional prosthetic components from PUSPADI-BALI. Conventional artificial limbs are then added mechanical components and electrical systems with integrated control systems. The deep learning neural network control system that was built is RNN-LSTM. The deep learning neural network control system uses the Multilayer Perceptron (MLP) concept. The research was conducted using two methods, namely the simulation method and the experimental method. In the design process, the structure of the leg, first analyzes and calculates the force (torque, etc.) on the bionic leg with an equilibrium diagram or Free Body Diagram (FBD), to determine the specifications of the DC motor and gearbox to be used. Then the bionic leg was designed through the Autodesk Inventor 2019 software. Furthermore, the simulation method was carried out in two categories, namely the static structure simulation category and the model simulation category. Static structure simulation uses ANSYS 2021 software which functions to determine and analyze the performance of the foot structure and the influence of the materials that make up the bionic leg. While model simulation serves to see the performance and accuracy of the neural network architectural model that has been built from the training dataset. This dataset was retrieved through a combination of sensors, namely the FSR402 sensor, a responsive force sensor for detecting muscle movements in the legs. The FSR402 sensor is placed around the thigh with a total of six sensors and produces data on the force of muscle contraction resulting from variations in leg movements. Furthermore, an MPU sensor is attached to the front of the thigh, which will produce position data that can represent leg movements according to the gait cycle. The FSR402 and MPU sensor placement scheme is illustrated in Fig. 1. Furthermore, the dataset collected is a training dataset based on a deep learning neural network with two models, namely ANN and LSTM. The two models will be compared based on the metric loss function MAE < 10 and R squared (accuracy) $\geqslant$ 90%. The model that has the smallest MAE loss function and the largest R squared (accuracy) will be deployed to the bionic leg. In this case, the research conducted using the simulation method will be validated with the experimental method to obtain accurate data and superior bionic leg products.

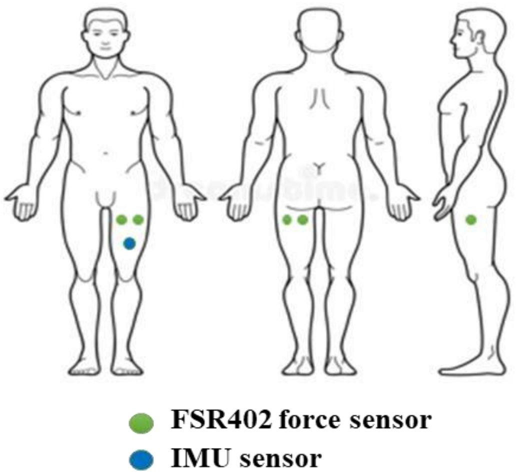

Figure 1. Allocation of the FSR402 sensor and the MPU sensor on the thigh.

B. Description of Prosthesis Leg

This research focuses on the development of a bionic leg design with a control system based on deep-learning neural networks. This bionic leg design consists of several main parts originating from PUSPADI-BALI including the polycentric type of knee joint, shank/leg length, and footsteps. The prosthesis foot has built using the intelligent material such as a Magnetorhelogical fluids [10, 11]. Design details and materials for the bionic leg components can be seen in Fig. 2. The material used in the manufacture of the bionic leg is a combination of Stainless Steel 304 (SS304) and Aluminum 6061. For the knee joint components, SS304 material is used, while other components such as shank/leg, and footsteps use aluminum 6061 as the material. The following is a specification of the material properties used in the preparation of the bionic leg described in Table I.

TABLE I. MATERIAL SPECIFICATIONS FOR BIONIC FOOT PRODUCTS

No	Specification	SS AISI 304	Al. 6061	Unit
1	Tensile Ultimate	505	310	MPa
2	Tensile Yield	215	276	MPa
3	Density	8.0	2.7	g/cc
4	Poisson's Ratio	0.29	0.33	
5	Modulus of elasticity	193	68.9	GPA

The design of the bionic leg can be seen in the image below:

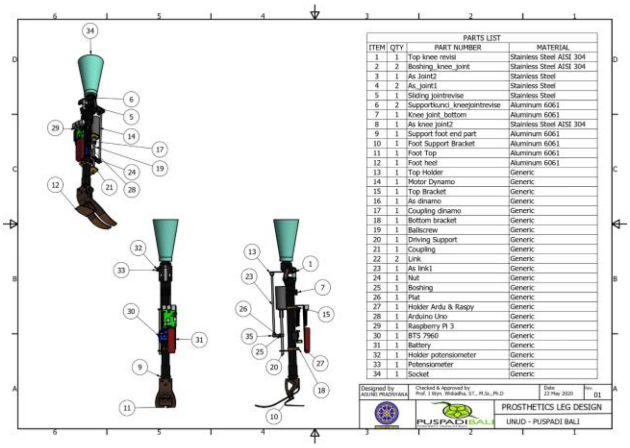

Figure 2. Design of a prosthesis leg.

C. Determination of Data Sources

In this paper, research data sources are needed, which include primary data and secondary data.

1) Primary Data includes

a. Data from neural network model simulations and training datasets using the Tensor flow and Google Colab modules. The resulting data obtained from this simulation include the Training dataset, Neural network architecture, Metric loss function Mean Absolute Error (MAE), and R Squared (Accuracy (%)) from RNN-LSTM models.

b. Data from experimental testing includes Observation data on the performance of the bionic leg structure and the performance of the deep learning neural network control system deployed on the bionic leg.

2) Secondary data

Data from international or national journals are referred to as the research for the process of simulating the foot structure with a variety of positions, namely midstance, heel strike, and toe-off [12]. In addition, the bionic leg structure test simulation uses the ISO 10328:2016 standard guidelines -Structural testing of Lower Limb Prostheses. This simulation uses ANSYS 2021 software. And research by [13] as a reference for the development of a conventional control system into PID control system. Regarding the deep learning neural network control system [14] and several journal references are used as references. From several national and international journals as well as previous research, this is used as a basis for research on bionic leg designs integrated with deep-learning neural network control systems.

D. Research Procedure

This research was conducted in 4 stages, namely, the first stage was to design and build a bionic leg, then the second stage was to simulate the static structure design, then the third stage was to assemble electronic circuits, and the fourth stage was to build and compare the two neural network control systems, both ANN models. and the RNN-LSTM model.

After completing the calculation and simulation planning process, then proceed to the electronic component design stage as shown in Fig. 3.

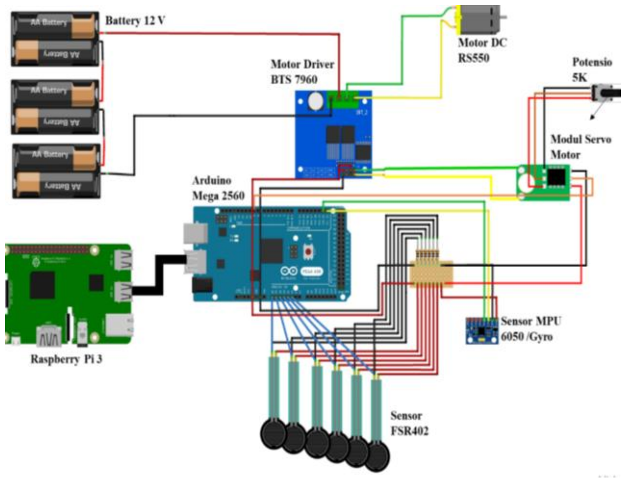

Figure 3. The electronic circuit of the bionic foot control system.

Fig. 4 shows the design of the RNN-LSTM neural network model applied to the bionic leg system. The general explanation of the RNN-LSTM model in this study is shown as follows:

- Input Layer: Seven inputs are represented by seven sensors placed on the thigh muscles
- LSTM Layer: Consists of a collection of repeatedly connected blocks, known as memory blocks. Each contains one or more repeatedly connected memories and three multiplicative units - input, output, and forget gates.
- Fully Connected Layer: The explanation is the same as ANN, this layer provides nodes that are directly connected to each node in the previous and subsequent layers
- Output Layer: The last layer of neurons which produces the output given to the model. Because it gives the same output as the ANN model, this layer dimension also has one dimension for a certain value.

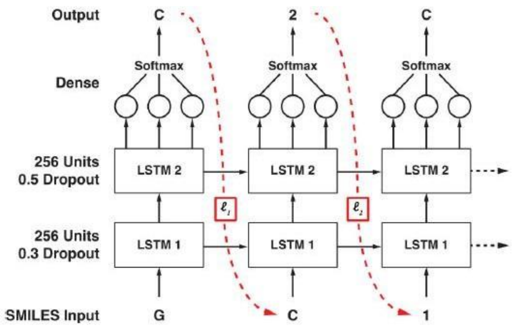

Figure 4. RNN-LSTM neural network architecture [15].

III. Results of Research

A. Prosthesis Leg Torque Calculation

Based on the dataset of the results of taking leg movements according to the gait cycle, it is found that the largest knee joint angle is 60° which will be mapped to the knee joint angle and the resulting torque value. This mapping value is shown in Table II.

TABLE II. Torque Values in the Prosthesis Leg Design

No	Position	Value θ	Torque (N. m)
1	Perpendicular (Midstance)	90	0
2	Bend 30 °	120	7
3	Bend 60 °	150	12

B. Retrieval of Deep Learning Control System Dataset

Because this neural network control system uses supervised learning, a dataset that is known for both input and output is needed. The dataset in this study was obtained through a control system with FSR402 and MPU 6050 force sensors connected to the Arduino Uno microcontroller. The stages of data collection or pre-processing can be illustrated in Fig. 5 and Fig. 6.

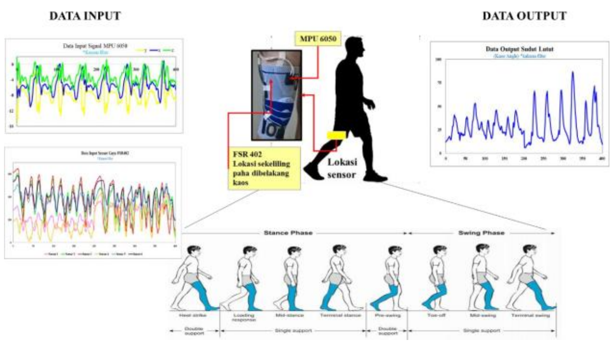

Figure 5. Schematic of data collection stages.

In Fig. 6, it is explained that six force sensors are placed around the thigh muscles and one MPU 6050 position sensor is placed on the front of the thigh. Then the process of collecting data on leg movements according to the gait cycle and also movements up and down the stairs. The input data obtained is in the form of a force signal and the position of the thigh when moving while the output is the angle data from the knee. Data collection is shown in Fig. 6.

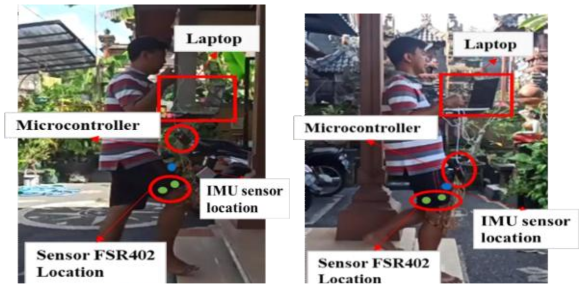

Figure 6. Foot movement data collection process.

Fig. 7 illustrates the results of the sensor values obtained and compared with the sensor values that have been filtered for the dataset pre-processing stage. With this filter, it can be seen that the sensor results obtained (raw) still have a high statistical noise value and are predicted to be smoother so that they will be more accurate in proceeding to the next stage, namely data processing.

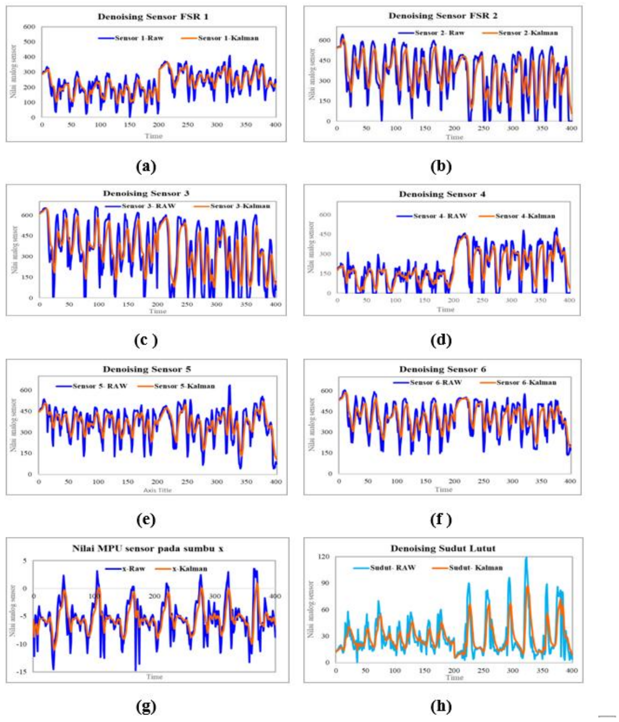

Figure 7. Sensor values highlighted and denoised with the filter from (a) Sensor 1 FSR401, (b) Sensor 2 FSR402, (c) Sensor 3 FSR402, (d) Sensor 4 FSR402, (e) Sensor 5 FSR402, (f) Sensor 6 FSR402, (g) MPU 6050 sensor (h) Knee angle (Knee angle).

C. Sensor Signal Data Processing and Processing

Fig. 8 shows the sensor signal data represented by 7 sensors is converted into a matrix form with the form Nx7 where N is the number of datasets. Furthermore, the data is split into 3 categories, namely data training, data validation, and data testing with the following ratios of 80% training, 10% validation, and 10% testing. Therefore, the training dataset has a total of 4411 data, a validation dataset of 508 data, and a testing dataset with a total of 508 data.

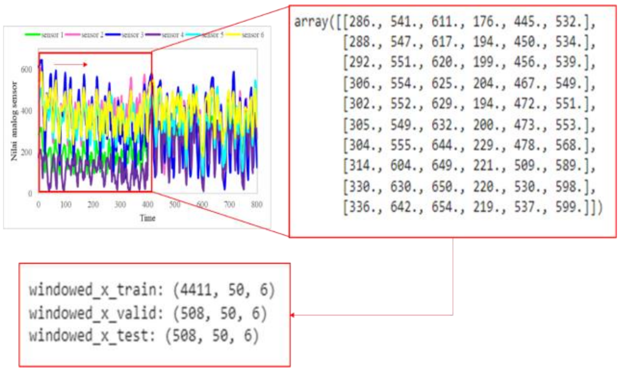

Figure 8. Data processing step.

D. *Results of Training and Testing Neural Network Models*

After building the neural network model, the data training process is carried out into the neural network model. The RNN-LSTM model training algorithm is shown in Fig. 9.

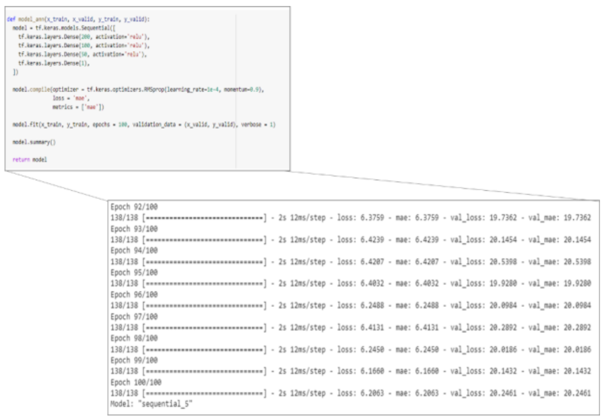

Figure 9. The RNN-LSTM model training process and algorithm.

Next, plot a graph between the training and testing processes to see how the RNN-LSTM model learns from the given dataset using the MAE (Mean Absolute Error) evaluation metric shown in Fig. 10.

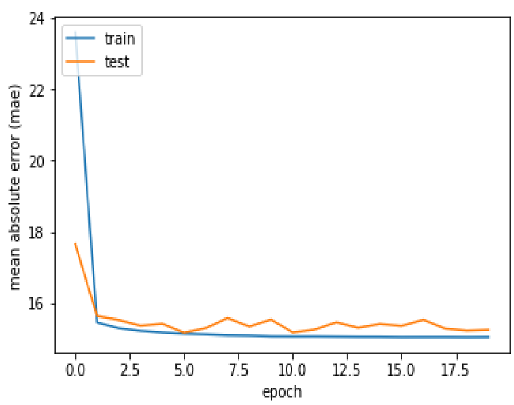

Figure 10. Plot of RNN-LSTM training and testing results.

The RNN-LSTM has MAE and R Squared values of 4.99 and 96.9%, respectively. Thus it can be seen that the RNN-LSTM model has an optimal value. Furthermore, the RNN-LSTM model will be deployed to a bionic leg control system.

IV. Discussion

A. *Bionic Foot Design Analysis*

In the results of the design of the bionic leg, it was found that the movement of the bionic leg that follows the gait cycle pattern, requires a force of motion in the form of a torsional moment. The moment of torque will increase as the load is given so that it will increase the power of the engine when it is working. This corresponds to the results of the torque calculation on the bionic leg design, whereas the leg position increases from 0° to 60° the torque value increases as shown in table II. DC motor torque affects the bionic leg movement so it is important to have a torque control system or gearbox to minimize damage due to torque overload.

The gearbox used must be in accordance with the torque design used so that it will be effective in selecting gearbox specifications which will ensure the safety of the gearbox and DC motor and bionic legs can move. The reduction gear ratio gearbox used is 67.4. Therefore, with the addition of a cordless gearbox component, the resulting torque (torque) is 28.3 Nm. with a rotational speed of 212 rpm. In the concept of walking gait cycle or walking conditions in general, the angle formed by the knee joint does not reach 90°, but 60° even below that angle. Thus it can be said that the specifications of the DC motor and gearbox components that are paired are according to plan and can move the bionic leg.

B. *Analysis of Closed Loop Systems in Neural Networks*

Fig. 11 shows a process block diagram and closed loop concept in a bionic foot control system.

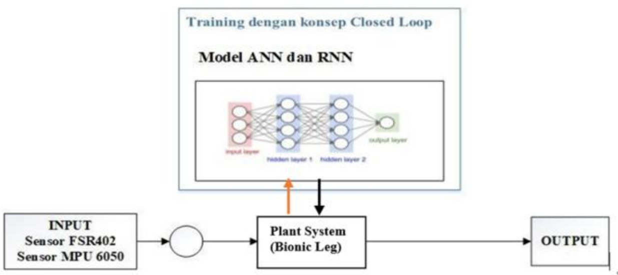

Figure 11. Block diagram of a neural network control system with a closed loop.

The image above is an illustration of the process in the form of a block diagram illustrating the overall process of the bionic leg control system. From the picture above it is explained that the closed-loop process will occur in the training process to get the minimum error value or the optimal neural network model. Furthermore, the neural network model will be able to provide decisions based on training results from experimental data, so that the bionic legs can move adaptively.

C. Analysis of Control System Test Results

From Fig. 10, it can be seen that the RNN-LSTM model is much better when training and testing are evidenced by the small MAE value during the testing process the MAE value is higher which allows the model to learn less or memorize (overfitting) so that when testing, the MAE value becomes tall. A metric evaluation indicator, namely R Squared, is also added to strengthen the performance status of the model so that it can be compared to a more optimal neural network model. The comparative value of the MAE and R Squared metrics evaluation in the two models is shown in Table III.

TABLE III. MAE AND R -SQUARED EVALUATION VALUES ON THE MODEL

Arsitektur Model	**Metrics**	
	Mean Absolute Error (MAE)	**R-squared (%)**
ANN (Baseline)	6.21	68.7 %
RNN-LSTM	4.99	96.9 %

The results of the evaluation of the two RNN-LSTM neural network models can be seen in Table III. The results refer to the metric loss function MAE and R squared. MAE is a method used to measure the prediction model's accuracy level. Results The smaller the MAE value, the more accurate the prediction model will be. Meanwhile, the R squared value indicates the influence of the independent variable (FSR402 & IMU sensor) on the dependent variable (knee angle). Based on this, the performance and performance of the RNN-LSTM are very good at 19.6% when viewed from the MAE category, because the error value generated by the RNN-LSTM is less. and in terms of R Squared (accuracy (%)), the RNN-LSTM is 41% better. This means that the RNN-LSTM model produces a strong independent variable (input) relationship in influencing the dependent variable (output). The RNN graph looks optimal because the model captures the dominant trend during training, and when given input testing, the model data produces the same output trend during training. So the RNN-LSTM neural network model is more optimal and reliable in producing output. And based on several studies, the RNN-LSTM is able to provide better results because this research uses a gait cycle which is one of the Human Activity Recognition (HAR) which has a work order/sequential. In addition, the LSTM layer consists of memory cells and gate units that manage and process memory in each neuron to overcome the occurrence of vanishing gradients when processing long sequential data. Therefore, the RNN-LSTM neural network model has more advantages than ANN.

V. CONCLUSION

Based on the results and discussion of the research that has been done, it can be concluded that the Neural network model RNN-LSTM has optimal performance with 4.99 MAE and 96.9% R-squared and also performance for HAR (Human Activity Recognition) data such as a gait cycle that has a work sequence.

In the future, the development of the strength of new materials for foot prostheses continues to be developed both through material strength simulation tests with ANSYST software and experimental tests in the materials laboratory. Nano-electrical components should be used to make the foot robot design lighter and more compact. Likewise, the forward force sensor can be implanted in the muscles so that it will make it easier for patients to use the prosthetic limb every day.

Further research on the use of neural networks and machine learning algorithms to improve the control and functionality of artificial limbs will continue to be used using certain methods so that the performance of the motion control system is achieved properly.

It is only fitting that the future development of more sophisticated and intuitive user interfaces for controlling prosthetic limbs should be enhanced by the use of brain-computer interfaces and other advanced technologies. Developments in the field of research and development of the Brain-Computer Interface (BCI) in the field of biomedical engineering continue to increase, especially in neuroprosthetic applications that aim to restore hearing, vision, and prosthetic limbs or hands.

In other developments, texture recognition of objects is important for prostheses to understand their surroundings and for prostheses to adjust their grip. Referring to these developments, the level of precision and ability to move prosthetic limbs and hands can be optimized by applying a neural network algorithm, this will increase the ability to move prosthetic limbs so that they can perform partial movements. In this way, the functional aspects of the leg or arm prosthesis can be improved. In addition, improving manufacturing systems using wearable devices and the Internet of Things can be done by integrating manufacturing processes that are integrated with mobile applications, such as when a patient wants to order a leg or arm prosthesis, simply use a mobile application to measure the dimensions of the leg or arm that will be designed to be prosthetic legs or arms quickly and easily. Another smart technology is using a vision camera to be able to detect the environment or objects around it so that the prosthetic limbs and hands quickly know what it is facing.

CONFLICT OF INTEREST

The authors declare no conflict of interests.

AUTHOR CONTRIBUTIONS

I Wayan Widhiada conducted the research; Wijaya Kusuma and Dwijana analyzed the results of the research; Agung Adnyana built the prosthesis leg, and Arya Putra has deep learning programming; all authors had approved the final version.

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