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THE MODEL OF LOCAL WISDOM FOR SMART WELLNESS TOURISM WITH OPTIMIZATION MULTILAYER PERCEPTRON

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ABSTRACT

This study focuses on the influence of variations in the number of hidden layers in the Artificial Neural Network (ANN) method on model performance and interpretability of results. The method applied involves integrating local wisdom to optimize the Artificial Neural Network (ANN) model. This approach combines locally relevant aspects with a conceptual framework to improve ANN performance. Evaluation of the results involves the performance metrics, MSE, MAE, RMSE, and F2 Score to find the best-hidden layer pattern in the Artificial Neural Network (ANN) model. The test results are based on a dataset with five indicators totaling 30 input layers and tested on the Multi Layer Perceptron (MLP) model. The results of testing a dataset with 30 input layers divided into 5 indicators produced performance metrics MSE 0.01346, MAE 0.09740, and RMSE 0.12094. The concept with a 16-hidden layer model pattern has high complexity and produces better predictions with fewer errors. Additionally, hidden layer 11 performs well, displaying a solid capacity to describe the variance in target data with an R2_Score of 0.17374. This produces two groups of ANN test results: the first group with improved accuracy (MSE, MAE, RMSE), and the second group highlights the optimal performance of hidden layers 16 and 11 (R2 Score). Local wisdom contributes to smart wellness.

Keywords: *Artificial Neural Network, Local Wisdom Integration, Performance Metrics, Hidden Layer Patterns, Multi Layer Perceptron*

1. INTRODUCTION

In an era of technological progress, efforts to synergize local wisdom with technological innovation are a current research topic [1]. Obstacles in synergizing local wisdom with technological advances can arise from several interrelated parameters, which include understanding local culture and values, infrastructure and access to technology, education and skills, regulations and policies, social change, and structural change [2]. By emphasizing local wisdom as a key element, it is hoped that this research will make a significant contribution to the development of ANN models that are more adaptive and effective, and able to deal with the dynamics of a particular context in an integrated local wisdom. An all-encompassing and flexible interactive learning [3] experience may be achieved by fusing local knowledge with technology and neural networks.

The focus of the research is to explore the impact of integrating local values on ANN model development [4], particularly when dealing with variations in the number of hidden layers, in order to model smart wellness. Evaluation of model performance is carried out using the Mean Squared

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Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 Score metrics [5] to obtain optimal model performance.

Human health and well-being have been reported to be two essential [6] aspects that impact people's lives and serve as the cornerstone of an effective and sustainable society. This perspective suggests that the main objective of efforts to improve the quality of life and achieve genuine well-being is wellness, a comprehensive term that encompasses physical, mental, emotional, social, and spiritual aspects [7]. In a modern era full of complexities and challenges, a deep understanding of the concept of wellness will open the door to innovative solutions that can guide us through a holistic and sustainable health journey [8].

Following this understanding, wellness becomes a journey toward optimal balance in various dimensions of life [9]. This includes physical body care, mental and emotional health, social connectedness, and the search for spiritual meaning in everyday life [10].

Although awareness of the importance of wellness is growing [11], health problems are becoming increasingly complex due to the progress and pressures of modern life. The main obstacles include an unhealthy lifestyle, job pressure, an imbalanced diet, and difficulty balancing work and personal life[12]. In the context of this research, we will conduct an in-depth study of the core problems, explore the root causes, and present an in-depth analysis, especially integrating local wisdom and technological advances smart wellness.

Various efforts have been implemented to address existing health problems. These measures include physical fitness programs, mental counseling, and support for a balanced diet [13]. Although beneficial in many instances, these approaches are frequently constrained and incapable of comprehensively addressing the whole range of health issues. The goals of this research are to better understand the benefits and drawbacks of various approaches, spot trends that might be used [14], and provide the groundwork for fresh, creative approaches to addressing societal health issues.

This study employs data mining to uncover skin preferences and reactions to natural compounds that are widely recognized in the community [15]. Through this method, researchers identify combinations of natural substances that are effective for particular skin types, forming the basis for developing more targeted facial care products[16]. The application of local wisdom in data mining also includes a deep understanding of the traditional values held by local communities [17], ensuring that treatment recommendations are not only physically effective but also linked to their rich cultural heritage. Thus, this method not only offers a way to take better care of your skin and nails [18], but it also promotes the application and preservation of local wisdom about health and appearance. The integration of local wisdom as one of the pillars of wellness in this research offers a revolutionary step towards holistic care that not only pays attention to physical aspects but also respects and utilizes the cultural richness of a community[19].

2. RELATED WORK

Regarding "wellness local wisdom" numerous research has been conducted to promote the use of local knowledge to enhance the welfare and health of communities.

This study explores the use of 73 medicinal plant species by "People-Forest-Miang" groups in the northern Thai region where Camellia sinensis var. asemia is grown, called Cha Miang. With a focus on musculoskeletal (30.14%), digestive (21.92%), and unidentified medicinal illnesses (15.07%) conditions, the diversity of plants utilized for diverse maladies is highlighted [20].

This study is on the traditional fermentation of Miang (tea leaves), in the community of Mae Kampong. This study blends qualitative investigation with a cross-sectional survey at Mae Kampong Village, Chiang Mai, Thailand, with 335 participants. Results show that Miang is consumed 93.7 percent of the time and plays a variety of functions in the economy, tourism, and cultural activities [21].

3. THEORETICAL BACKGROUND

3.1 Smart Wellness

Connecting the SMART idea and wellness requires the Internet of Things (IoT) [22] [23]. Smart wellness refers to the use of technology as a useful instrument to improve people's well-being and advance health services [24]. Within this paradigm, medical record data analysis may be supported using artificial intelligence and machine learning [25]. Smart wellness can also provide personalized recommendations, including changes to lifestyle, sleep patterns, or types of physical activity that can help achieve health goals [26]. Smart wellness the goal of local wisdom, is to develop solutions that uphold traditional values, fit the cultural context of the area, and address community health issues in a comprehensive way [27].

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3.2 Local Wisdom Wellness

The local wisdom wellness model is an approach to health policy that utilizes indigenous knowledge [28]. As a component of indigenous knowledge, Javanese script has a strong connection to the advancement and empowerment of welfare, including elements of health (wellness) [29]. Health is defined as a state of complete equilibrium between the body, mind, and spirit in addition to the absence of sickness in the context of well-being [30]. The local wisdom wellness paradigm emphasizes the fusion of traditional practices and local knowledge with contemporary notions of health [31]. Cooperative efforts with local communities are part of the model's implementation, which aims to comprehend and investigate traditional knowledge and health practices.

3.3 Theoretical Data Mining.

Data mining is the process of looking for patterns, trends, or important information in large amounts of data by examining and analyzing it [32]. Data mining is frequently employed in the context of recommendations to find trends in user behavior and preferences [33].

3.4 Metode Artificial Neural Network (ANN).

Sharing information is a key component of collaborative learning [34], and ANN techniques can enhance analysis and suggestions by leveraging collaborative efforts. Artificial Neural Networks (ANNs) with deep architectures are used in deep learning to model complicated data [35]. The Artificial Neural Network (ANN) is a technique in AI that mimics the architecture and functionality of natural neural networks [36]. Throughout the training process, the weights of each connection between the layers of artificial neurons that make up this model can be changed [37]. In the context of data mining, these networks are a highly useful tools since they can handle complicated information and represent non-linear correlations in data [38].

Since ANNs can handle complicated patterns and non-linear connections among characteristics in the data, they are important in the context of data mining [39]. By providing the model with known inputs and outputs throughout the ANN training phase, weights may be adjusted to enable the network to create output that is nearly identical to the intended aim [40]. This makes it possible artificial neural networks to learn from current data and produce precise classifications or predictions.

The study investigates the potential of artificial neural networks in data mining to enhance the quality of analysis and recommendations [41]. This strategy concentrates on how artificial neural networks can comprehend non-linear relationships, find intricate patterns, and extract hidden information from datasets that may be challenging for traditional analytic techniques to access [42]. To maximize the benefits of using artificial neural networks in the context of data mining, this study also considers a variety of neural network designs and architectures in addition to ideal training techniques [43] [44]. Inspired by the complex operations and activities of the human brain, artificial neural networks are created as a depiction of a distributed network model [45].

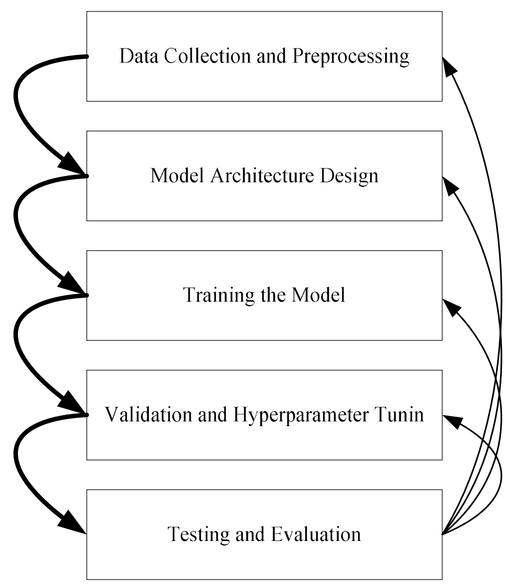

Figure 1: Stages of Using the ANN Method

3.5 Multilayer Perceptron

Inside artificial neural networks, MLP is one kind of architecture [46]. The structure in MLP is the input layer, hidden layer, and output layer [47]. Training MLP needs the use of learning methods, like backpropagation [48]. By altering the network's weights and biases, backpropagation reduces the error between predicted and actual values [49]. An activation function in the hidden layer and output layer determines the output of each neuron by analyzing its input [50]. Every neuron in the output layer and hidden layer has an activation function that chooses the neuron's output depending on its input [51]. ReLU (Rectified Linear Unit), hyperbolic tangent (tanh), and sigmoid are a few examples of popular activation functions [52]. MLP has various applications, such as pattern recognition, regression, and classification [53]. Further, overfitting is a common issue in MLP training, where the model learns the training data too well and performs poorly on new data [54]. MLP can handle complex issues, but it requires a significant amount of data and training time. Additionally, selecting an appropriate network layout and avoiding overfitting are major challenges [55].

In the hidden layer, the nodes' input (α_{ij}^{l}) determined by combining their output from the preceding layer (α_i^{l-1}) in a linear fashion. This is done by adding intercept (b_j^l) and using an activation function (fx) :

$$\alpha\frac{l}{ij} = f(\textstyle\sum_i \alpha\frac{l-1}{i} \,.\, \omega_{ij}^l + b_j^l) \quad (1)$$

α_{ij}^{l} output from to- j node in the l the layer
α_i^{l-1} output from node to-I the l-1 the layer
ω_{ij}^{l} weights that connect the nodes to-l the l-1 the layer to-j the l the layer
b_j^l intercept (biased) for node to-j in the l the layer
f activation function

The nodes in the output layer's output layer are computed using Formula 2.:

$$\alpha_j^L = f(\textstyle\sum_i \alpha_i^{L-1}.\, \omega_{ij}^L + b_j^L) \quad (2)$$

α_j^L output from node to-j output layered L

3.6 Model Evaluation

The mean absolute error (MAE) is a commonly used assessment measure to determine the extent to which a model's predicted values differ from the actual values in a dataset. It is calculated by averaging the absolute differences between each prediction and the actual value. The MAE formula can be expressed mathematically as follows [5].

$$MAE = \frac{1}{n}\textstyle\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (3)$$

n number of samples in the dataset
y_i the true value of the to-i sample.
$\hat{y}_i$ predicted value produced by the model for the to-i sample.

MAE presents an indication of the average prediction error, regardless of the direction of the error (positive or negative).

Mean Squared Error (MSE) is a commonly used evaluation metric to measure the accuracy of a model's predictions by considering the magnitude of the error and giving greater weight to larger errors. MSE is calculated by taking the average of the squared differences between the predicted value and the actual value. Mathematically, the MSE formula can be explained as follows [5].

$$MSE = \frac{1}{n}\textstyle\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (4)$$

n number of samples in the dataset
y_i the true value of the to-i sample
$\hat{y}_i$ predicted value produced by the model for the to-i sample

MSE has several advantages, one of which is that the difference between the prediction and the actual value is squared so that a larger error will make a larger contribution to the MSE value. However, MSE has the weakness that it is susceptible to outliers because the square can magnify the impact of large errors.

Root Mean Squared Error (RMSE) is an evaluation metric that is often used to measure the extent of the difference between the predicted values of a model and the actual values by giving greater weight to significant errors. RMSE is calculated by taking the square root of the Mean Squared Error (MSE). Mathematically, the RMSE formula can be explained as follows [5].:

$$RMSE = \sqrt{MSE} \quad (5)$$

MSE is the previously calculated Mean Squared Error. RMSE has several advantages, one of which is that the result has the same units as the original target variable, making it easier to interpret in the context of a specific problem. RMSE also provides a more sensitive picture of significant errors due to the quadratic effect on large errors.

R-squared Score, also called the coefficient of determination, is an evaluation metric that provides information about how well a regression model fits the data. The R2_Score value ranges from 0 to 1, where a value of 1 indicates that the model fully explains the variability of the data, while a value of 0 indicates that the model does not make any contribution in explaining the variability. R2_Score value can be calculated using the following formula (6).

$$R2_{score} = 1 - \frac{SSR}{SST} \quad (6)$$

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SSR is the sum of squared residuals, which is the sum of the differences between predicted values ($\hat{y}_i$) and the actual value (y_i) which has been squared,

SST is the sum of the squared total, which is the sum of the differences between each true value and the average true value ($\overline{y}$) which has been squared.

Intuitively, R2_Score measures how much variability in the target variable that can be explained by the model. A high R2_Score value indicates that the model can explain most of the variation in the data, while a lower value indicates that the model is less effective in explaining the variation.

3.7 Regression

Regression analysis is used to simulate the connection between one or more independent variables, also known as feature or input variables, and a dependent variable, also known as output or target variables. A regression model's primary objective is to identify patterns or correlations between these variables to forecast or estimate the value of the dependent variable when the independent variable's value is known [56]. Regression models can be either linear or non-linear, depending on the nature of the relationship between the independent and dependent variables [57]. A non-linear regression model allows the relationship between the variables to take the shape of a polynomial or a curve, however, a linear regression model assumes that the relationship between the variables is linear [58].

In the context of simple linear regression [59], involving only one independent variable and one dependent variable, the formula can be written as follows:

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{7}$$

y dependent variable (target)
x independent variables (features)
β_0 intercept (value y when x =0)
β_1 regression coefficient that measures the extent y changes when x changes.
ε errors or residuals, which represent uncertainties or factors that cannot be explained by the model.

For more complex regressions [59], involving more than one independent variable or feature, the general formula can be expressed as: (8).

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon \tag{8}$$

$x_1, x_2, .. x_n$ independent variables
β_0 intercept
$\beta_1, \beta_2, ... \beta_n$ regression coefficient for each independent variable, ε is the error or residual.

The process of training a regression model involves adjusting the coefficient values (β) so that the model provides predictions that are as accurate as possible regarding the value of the dependent variable.

4 METHODOLOGY

4.1 Data Collection

In numerous countries, data on wellness tourism is inaccessible due to the high cost of measurement devices [60]. Access to this information is necessary for the public to determine whether action is required. Therefore, this research aims to determine the need for health service action based on available data.

A dataset of healthcare transactions from SPA Wellness was used in this study, particularly the data from transactions that occurred throughout the previous three years. The dataset reached 1110 transactions, which included relevant information regarding health services at the SPA. The main focus of this study was to analyze primary data and gain a comprehensive understanding of the trends and patterns of health transactions that occurred at SPA Wellness during the specified time period. The research aims to make a significant contribution to the understanding of health services in SPA and wellness environments by utilizing this extensive dataset.

As shown in Table 1, the study framework uses five indicators, totaling thirty variables that serve as input layers. This study makes use of a framework with five indicators, each of which consistss of several variables that are used as input for data analysis. This study makes use of a framework with five indicators, each of which consists of several variables that are used as input for data analysis Table 1 which is a crucial resource for understanding the components of the study and the framework of the research, contains comprehensive information on key indicators and input variables.

Table 1: Input layer indicators and variables

Indicator	Variable
Skin type	1. Dry skin 2. Normal skin

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	3. Oily skin
Skin and nail disorders	1. Blood vessels appear. 2. chalk hooves/horns 3. calluses (hands) 4. smallpox scar 5. brittle nails 6. ingrown toenail 7. white speckled nails 8. beauty spot 9. transverse striped nails 10. wavy nails 11. cracks on the heels of the feet 12. calluses (feet) 13. katimumul (fisheye)
Finger shape	1. big 2. small 3. long 4. short 5. pointed
Nail shape	1. round 2. oval 3. rectangle 4. nails are maintained
Contraindication	1. allergy 2. diabetes 3. nail fungus 4. heart disease 5. hypertension

This dataset includes details on skin type, problems of the skin and nails, nail and finger shapes, and potential contraindications. Aspects such as skin type, conditions of the skin and nails, nail and finger shapes, and contraindications can all be linked to variables a1 through e5. Specification values are summarized statistically using the Mean and Coefficient variables. Variable Y is a target variable that might point to a certain label or category outcome. Variable Y is a target variable that might point to a certain label or category outcome. One observation is shown in each row, along with values for the characteristic and target variable. Additional examination may reveal trends or connections in this data. A summary of the overall properties of the observed variables is also given by the average value (Average) of this dataset.

4.2 Constructing a Multilayer Perceptron Model

The model developed can be used to classify whether there is a need for health service action at SPA Wellness in general to build an MLP model, as in Figure 2.

The classification of the dataset aims to recognize and comprehend potential patterns and connections among the features documented within it [61]. The values of indicators a1 through e5, which reflect skin type, diseases of the skin and nails, nail form, finger shape, and contraindications, may be analyzed to provide advice on what the influencing factors impact the intended outcome, which is represented by the variable Y. Furthermore, the classification goal entails determining whether these variables exhibit significant correlation patterns [62], which may shed additional light on the determinants about skin type, disorders of the skin and nails, and other health conditions that are represented in datasets. Based on the data in the dataset, it is believed that this classification would aid in improved decision-making about skincare and a deeper knowledge of individual features.

The data collection method for the dataset involves documenting details on skin type, skin and nail problems, nail and finger shapes, and contraindications to certain observations. The Sum and Average variables provide a statistical explanation of the distribution of these values, whereas the binary indicators a1 through e5 indicate whether specific traits are present in each observation. To find any patterns or trends that may exixt, this dataset's numerous examples with different values for each characteristic are examined. In addition to processing medical information or transaction records about services rendered, this data gathering may also entail direct recording or observational methods about the state of the nails and skin. The purpose of this data collection was to provide a solid basis for future research and to offer valuable insights into the factors that affect skin conditions and overall health.

The data processing and cleaning process is a critical stage in ensuring the accuracy and quality of the dataset before further analysis is carried out [63]. The first step is to manage invalid or missing values for each variable. Next, data standardization is performed to ensure that the variables are consistent and uniform. To ensure suitable and representative results, extra care may need to be given to the Sum and Average variables. This process involves identifying and addressing outliers that may affect the analysis results. Then, select the factors that are most relevant or the ones with a significant impact on the target variable Y. Finally, eliminate duplicates and entry errors that may affect the analysis findings. This procedure establishes a solid basis for obtaining accurate and meaningful insights into the factors that affect skin type, skin and nail issues, and other health aspects represented in the dataset by ensuring the integrity and quality of the information.

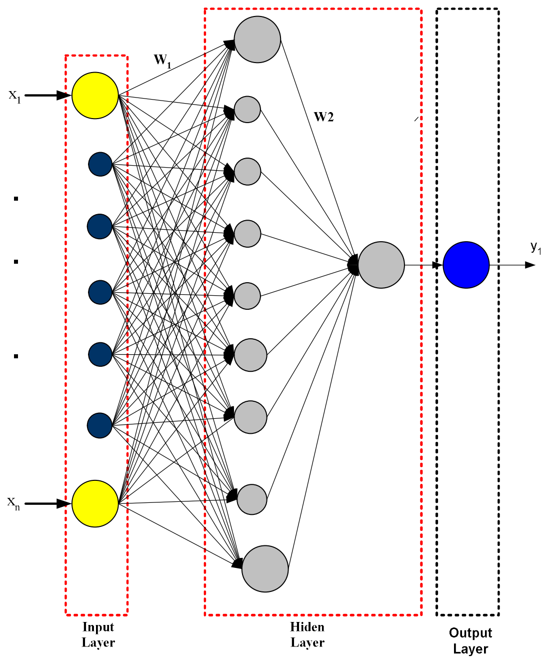

Figure 2 : Multilayer Perceptron (MLP) Architecture Model

Sharing datasets is a necessary first step in carrying out efficient analysis. This dataset may be split as divided into two primary groups: the training data, which makes up 70% of the total, and the test data, which makes up the remaining 30% the data. A model or algorithm that will eventually be utilized to provide predictions or recommendations [64] is trained using training data. To reduce bias in the model at this point, it is crucial to consider a fair percentage between positive and negative classes for the target variable Y. However, test data is used to evaluate how effectively the model has been trained to provide accurate predictions on examples that were not part of the training process. Careful and fair sharing of this dataset helps in mitigating the risk of overfitting and improves model generalization to new, never before seen data. The model should produce consistent predictions for the target variable category Y using a solid dataset-sharing approach.

Network architecture design is a key step in developing predictive models or data analysis. Machine learning or deep learning techniques may be used depending on the complexity and nature of the data [65]. First, qualities relating to skin type, problems of the skin and nails, finger and nail shapes, and contraindications were represented by the indicators a1 through e5 in the input layer. Meanwhile, the hidden layers could be designed to explore and extract complex patterns or relationships between these attributes. The output layer included a target variable Y, indicating the outcome category. To maximize model performance, further considerations, such as the activation function and other parameters, were required. To improve model generalization, it was necessary to perform cross-validation methods and parameter adjustment. The model was expected to be capable of identifying complex patterns in the data and generating accurate predictions for the skin and medical conditions included in the dataset by constructing an appropriate network architecture.

The initialization of the weights is the first stage in creating a network-based model. During this initialization, starting values must be specified for the parameters that will be changed during the training process. Using the appropriate weight initialization procedures can affect the convergence and overall performance of the model. The next stage is the model training process, which involved splitting the dataset into test and training sets based on a preset ratio. The model is trained using the training data, allowing it to adjust its weights to patterns in the data. This process involves repeated iterations and optimization of model parameters using algorithms, such as stochastic gradient descent or other variants. Cross-fold validation can also be applied to avoid overfitting and test model performance more objectively. Thus, by carefully initializing the weights and thoroughly training the model, it is expected that the model can effectively learn from the dataset and make accurate predictions regarding the target variable category Y, which representes skin and health conditions.

The next step in developing a network-based model is to validate and tune hyperparameters. The purpose of validation is to assess the model's performance objectively and determine if it can generalize effectively to new data. Model evaluation may be done with consideration for dataset fluctuations by using cross-validation techniques. In addition, hyperparameter tuning refered to the process of determining the optimal values for model parameters such as the learning rate, number of layers, and neurons in the network that are not discovered during training. This process involves conducting multiple tests with various combinations of hyperparameters and selecting the combination that produces the best results on the validation data. The model should be optimized to ensure consistent and accurate predictions on new data, including test data that was not used during training. By carefully

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validating and fine-tuning the hyperparameters, we hoped to enhance the model's performance and enable it to handle the various conditions in the dataset. This will result in more reliable solutions related to skin type, skin disorders, nails, and other health factors reflected in the dataset.

In the context of model evaluation for the dataset in the table above, several relevant performance metrics are used to measure the accuracy and effectiveness of the model. Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) are metrics commonly used to evaluate the extent to which a model is close to or far from the true value in a regression prediction. These values measure the deviation between predicted values and actual values, providing an idea of how well the model can model relationships between variables in a regression context. Next, the model's performance on the classification task is assessed using the R2_Score measure. With an emphasis on reducing false positive mistakes, this statistic gives accuracy a higher weight than recall. In the case of this dataset, where the target variable Y indicates a particular category of skin diseases and health this is extremely helpful.

By evaluating the model using these measures, we can obtain a more thorough understanding of its efficacy in predicting regression results or categorizing test data. The results of this evaluation guided further improvements to the model or iterations in the development process. By considering various metrics, it is hoped that the model can provide accurate and reliable solutions related to the skin and health information contained in the database.

The implementation of a network-based model comprises several critical stages. Firstly, the network architectural design is established by identifying the input layer, hidden layers, and output layer based on the properties found in the dataset. To initiate the training process, weight initialization is carried out, which involves selecting suitable algorithms and optimization strategies. The dataset is partitioned into training and test data in a 70:30 ratio. The model was then trained using the training data to adjust its weights to patterns in the data. During this training procedure, assessment metrics, such as MSE, MAE, RMSE, and F2_Score, are monitored. Evaluation metrics are utilized to ensure optimal convergence. After completing the training, the model's performance and forecast accuracy are evaluated using test data. The aim is to create a model that can effectively comprehends and responds to the complexity of the dataset through meticulous iteration and hyperparameter tweaking, providing reliable answers related to skin and health concerns.

5 RESULTS AND DISCUSSION

Table 1 shows the evaluation results of the performance of a neural network model with variations in the number of hidden layers, using various metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 Score..

Table 1: Test Results

Hidden Layer	MSE	MAE	RMSE	R2_Score
1	0.01806	0.09681	0.12548	0.03645
2	0.01578	0.09769	0.12438	0.09567
3	0.01677	0.10592	0.12631	0.02225
4	0.01415	0.10311	0.12266	0.20550
5	0.01478	0.09421	0.12691	0.11426
6	0.01392	0.09475	0.12130	0.09673
7	0.01507	0.09794	0.11849	0.09391
8	0.01497	0.09423	0.11936	0.07377
9	0.01480	0.09286	0.11938	0.08599
10	0.01432	0.10068	0.11469	0.09516
11	0.01450	0.09183	0.12847	0.17374
12	0.01681	0.09685	0.12759	0.11832
13	0.01363	0.09570	0.12070	0.04640
14	0.01565	0.09791	0.11986	0.03380
15	0.01364	0.09534	0.12440	0.14509
16	0.01346	0.09740	0.12094	0.18164
17	0.01407	0.09640	0.11990	0.16988
18	0.01497	0.10623	0.12323	0.08688
19	0.01703	0.09900	0.12291	0.06586
20	0.01511	0.09865	0.12713	0.16734

Mean Squared Error (MSE) is a metric that measures the average of the squared differences between predicted values and actual values. The lower MSE value better model's performance. Mean Absolute Error (MAE) is a metric that measures the average absolute difference between predicted and actual values. Just like MSE, the lower MAE value the better model performance. Root Mean Squared Error (RMSE) is the square root of MSE and indicates the distribution of errors. As with MSE and MAE, a lower RMSE value represents better model performance. The R2 Score indicates how well the predicted value matches the actual value, with a score of 1 indicating a perfect fit and a score of 0 indicating that the model is no better than simply predicting the mean of the target value.

Detailed analysis of the table shows variations in the performance of neural network models with various numbers of hidden layers. At a low level of complexity, such as in a model with one hidden layer, the MSE value of 0.01806 is quite high, indicating the model's in accuracy in predicting the data. MAE and RMSE at this level are also relatively high, respectively 0.09681 and 0.12548. Additionally, the low R2_Score (0.03645) indicates the model has limitations in explaining variations in the data.

As hidden layers are added up to 4, we see significant improvements in model performance. The MSE, MAE, and RMSE values consistently decrease, indicating that the model is increasingly able to minimize prediction errors. At the same time, the R2_Score value increases substantially, to reach 0.20550, indicating that the model's can better explain the variations in the target data. This indicates that increasing model complexity can bring significant benefits at the performance level.

However, it is important to note that increasing the number of hidden layers does not always lead to significant performance improvements. While the model with 16 hidden layers demonstrates excellent performance with low MSE, MAE, and RMSE values, the high R2_Score value (0.18164) suggests the possibility of overfitting. Therefore, the selection of the number of hidden layers must be carefully considered, taking into account the trade-off between improved performance and the risk of overfitting. Finally, these results highlight the significance of validating models on distinct test datasets to ensure good generalization to new data.

6 CONCLUSION

In summarizing the table analysis, it can be concluded that the model with 16 hidden layers shows the best performance with an MSE value of 0.01346, MAE of 0.09740, and RMSE of 0.12094. These results confirm that high model complexity, which is reflected in a larger number of hidden layers, contributes to better prediction capabilities in minimizing squared and absolute errors.

However, it is worth noting that the model with 11 hidden layers also stands out with an R2_Score value of 0.17374, indicating a good ability to explain variations in the target data. This means that this model can provide a strong representation of patterns that emerge in the data. This conclusion reinforces the idea that selecting the best model is not only limited to prediction error criteria but also considers the model's ability to explain variations and patterns contained in the dataset.

With these concrete values, researchers can consider the trade-off between model complexity and predictive performance and select the model that best suits the goals and nature of the task at hand. The use of independent test datasets and testing of models under various conditions remains an important step to ensure the reliability and generalizability of the developed models. The Transformer Model is a viable option for characterizing and comprehending textual material related to local wisdom. Its potential for advancing the concept of smart wellness is significant.

AUTHOR CONTRIBUTION STATEMENTS

Author 1: In my capacity as a writer and manager of field data collecting, local stakeholder interviews, and local wisdom ideas for smart tourism. Ensuring the correctness and consistency of research results is a responsibility that goes beyond writing reports, interpreting data, and responding to criticism from other writers and journal reviewers
Author 2: strengthen core research concepts by establishing a theoretical framework, synthesizing the literature, and providing analytical contributions in the interpretation of data.
Author 3: strengthen the literature review in this research, detailing key concepts, identifying knowledge gaps, and linking literature findings to the research framework.
Author 4: coordinated the model design, collected the necessary data, supervised the statistical analysis process, and served as the primary editor of the manuscript

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