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MACHINE LEARNING MODELS FOR PREDICTING STRESS VALUE IN THE TENSILE STRENGTH OF BIOFILMS FROM STARCH DAN HAIR WASTE

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ABSTRACT

Biofilms, structured communities of microorganisms, have emerged as a subject of significant interest across various industries due to their unique biodegradable and sustainable characteristics. Hair waste is an incredibly rich source of keratin, and this abundance makes it a promising candidate as a fundamental building block for the development of biodegradable plastics. This study focuses on sustainable biofilms derived from biodegradable materials, specifically a unique combination of starch and hair waste. Machine Learning models, implemented in RapidMiner, were utilized to predict the tensile strength of these biofilms, with the goal of enhancing quality control in their production. Neural Networks and Deep Learning methods were employed to compare their predictive capabilities, assessing both their strengths and limitations. Through rigorous data collection, feature identification, and detailed data analysis, critical factors influencing the quality of the biofilms were identified. The results revealed the remarkable predictive accuracy of the Neural Net model, particularly for Ratio 40, while the performance of the Deep Learning model varied across different ratios. The lower RMSE of the Neural Net model indicated a more precise alignment between the predicted and actual values, distinguishing it as the superior model. This research contributes to the advancement of sustainable biofilm development, offering eco-friendly solutions through the use of unconventional materials. Both models offer valuable predictive capabilities, and the choice between them may depend on the specific requirements and contexts of the application. In conclusion, the performance of the Neural Net and Deep Learning models in predicting stress in tensile strength varies across different ratios.

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Introduction

Biofilms, structured communities of microorganisms, have emerged as a subject of significant interest across various industries due to their unique biodegradable and sustainable characteristics (Shineh et al., 2023). These biofilms present a promising avenue for replacing conventional non-biodegradable materials in applications ranging from packaging to medical devices, offering the potential for reduced environmental impact and enhanced sustainability (Mastrolia et al., 2022). Notably, biofilms crafted from unconventional and waste materials have garnered attention as an eco-friendly approach to manufacturing practices (Elmi et al., 2017).

Starch, a readily available and renewable resource, serves as a common base material for biofilm production due to its biodegradability and compatibility with various additives (Jayarathna et al., 2022). In this context, the integration of hair waste, a typically discarded material, has been explored as an innovative method for enhancing the mechanical properties of biofilms. This approach not only addresses waste disposal concerns but also contributes to the tensile strength and structural integrity of the resulting biofilms (Calegari et al., 2017).

Hair waste is an incredibly rich source of keratin, and this abundance makes it a promising candidate as a fundamental building block for the development of biodegradable plastics. Keratin, a fibrous structural protein found in human hair and various other natural sources, offers unique properties that can be harnessed to create environmentally friendly and sustainable bioplastics (Chilakamarry et al., 2021). Keratin's abundance in hair waste is a crucial advantage for sustainable material production. This natural protein, which constitutes a significant portion of hair, is exceptionally resilient and durable. When extracted from hair waste, keratin can be transformed into biodegradable plastics, which hold immense potential in addressing environmental concerns associated with non-biodegradable plastics (Utami et al., 2021).

These biodegradable plastics derived from hair waste can serve as a practical alternative to traditional plastics that contribute to pollution and environmental degradation. Keratin-based bioplastics are not only eco-friendly but also have the advantage of being sourced from a readily available waste stream. This means that they can reduce the environmental footprint by repurposing a resource that is often discarded (Utami et al., 2022). The utilization of keratin-based biodegradable plastics represents an innovative step toward sustainability in material science. Transitioning from this environmentally conscious approach, we delve into the realm of machine learning to further optimize and enhance the properties of these biodegradable materials.

Machine Learning (ML) models, including neural networks and Deep Learnings, have emerged as powerful tools for predicting and optimizing material properties (Stergiou et al., 2023). By training these models on relevant datasets, it is possible to develop accurate predictions for the tensile strength of biofilms. In this study, we leverage the capabilities of RapidMiner, a data visualization and analysis tool, alongside ML models to predict the tensile strength of starch and hair waste biofilms. This research aims to enhance the understanding of the factors affecting biofilm quality, facilitating improved manufacturing processes (Sudirman et al., 2018).

Predicting stress value in the tensile strength of biofilms holds a pivotal role in optimizing their application. Machine Learning (ML) models have emerged as potent tools in material property prediction and optimization. By training these models on relevant datasets, it becomes feasible to derive precise forecasts regarding the tensile strength of biofilms (Al-Kharusi et al., 2022). This study embarks on an exploration of ML applications, employing neural networks, Deep Learnings, and the data visualization prowess of RapidMiner to predict the stress value in tensile strength of biofilms derived from starch and hair waste.

Neural networks, inspired by the human brain's neural structure, are a type of ML model known for their ability to capture complex and non-linear relationships in data (Kinza, 2007). They consist of interconnected layers of artificial neurons that learn from data through a process of forward and backward propagation. Neural networks have shown great promise in predicting material properties by uncovering intricate patterns within datasets (Rapidminer, 2011). In contrast, Deep Learnings are another type of ML model that follow a more interpretable path. They break down data into a series of hierarchical decisions, leading to a final outcome. Deep Learnings are valued for their transparency and ease of interpretation, making them a favored choice when the need for explaining

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the reasoning behind predictions is paramount (Marimuthu et al., 2022).

This research aims to provide a comparative analysis of the predictive capabilities of neural networks and Deep Learnings in predicting stress in the tensile strength of biofilms. Through a systematic examination of their performance, we seek to identify the strengths and weaknesses inherent in each approach. Such insights have the potential to revolutionize the sustainable materials development landscape, offering profound contributions to the production of environmentally friendly biofilms sourced from unconventional raw materials. Furthermore, the urgency of this research lies in addressing the growing need for eco-friendly materials that can replace conventional plastics, thus reducing environmental impact. As global waste disposal challenges persist, finding innovative ways to repurpose materials like hair waste into biodegradable plastics becomes increasingly critical for advancing sustainable manufacturing practices.

Research Methods

Data Collection and Preparation

1. Data Source

The research employed a dataset containing information on the composition, manufacturing parameters, and tensile strength of biofilms made from starch and hair waste. This dataset was collected through experiments and measurements specifically for this study. The data collected are Time (s), Load (N), Stress (MPa), Extension (mm) and Percentage Strain for each concentration. The concentrations are 20, 40, 60, 80 and 100 ratios of glycerol as a solvent and the material in which starch and hair waste. Hair waste samples were obtained from local salons and wig manufacturing facilities. The hair waste was thoroughly cleaned to remove any contaminants and then air-dried to a constant weight.

Table 1. Tensile Test Data Attributes

Column	Type	Description
Time (s)	Real	represents the duration of the biofilm tensile test, measuring how long the material is subjected to an applied force.
Load (N)	Real	measures the force applied to the biofilm during the tensile test.
Stress (MPa)	Real	measure of the internal resistance within the biofilm material as it undergoes deformation due to the applied load
Extension (mm)	Real	represents the change in the biofilm's length during the tensile test.
Percentage Strain	Real	quantifies the amount of deformation in the biofilm as a percentage of its original length.

Data Preprocessing

Prior to analysis, the dataset underwent thorough preprocessing. This included handling missing values, standardizing data, and encoding categorical variables as needed. Data cleaning was executed to ensure the dataset's integrity and quality.

Figure 1. Dataset from Tensile Strength

	ï»¿Time (s) real	Load (N) real	Stress (MPa) real	Extension (mm) real	Percentage Str... real
1	0.134	-0.381	-0.007	-0.431	-0.359
2	0.268	-0.381	-0.007	-0.431	-0.359
3	0.402	-0.462	-0.008	-0.428	-0.356
4	0.536	-0.559	-0.010	-0.424	-0.354
5	0.670	-0.656	-0.012	-0.410	-0.342
6	0.804	0.698	0.012	-0.392	-0.327
7	0.938	1.199	0.021	-0.369	-0.307
8	1.072	1.699	0.030	-0.350	-0.292
9	1.206	2.200	0.039	-0.325	-0.271
10	1.340	2.700	0.048	-0.299	-0.249
11	1.474	3.201	0.057	-0.280	-0.233
12	1.608	3.701	0.066	-0.262	-0.218

Feature Selection

1. Feature Engineering

The dataset was examined to identify relevant features that may impact the tensile strength of the biofilms. Features related to starch-hair waste and glycerol ratio, processing temperatures, and curing times were identified as key predictors of tensile strength.

2. Machine Learning Models

RapidMiner, a robust and user-friendly data science platform, was employed as the primary tool for creating, evaluating, and deploying machine learning models. RapidMiner offers a range of data analysis and modelling capabilities, making it well-suited for this research.

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Figure 2 RapidMiner Application Version 10.2

3. Model Selection

Two primary machine learning models were utilized for predictive modeling: Neural Networks and Deep Learnings. Neural Networks are powerful at capturing complex relationships in data, while Deep Learnings are known for their interpretability. This choice allowed for a comparison of model performance and interpretability.

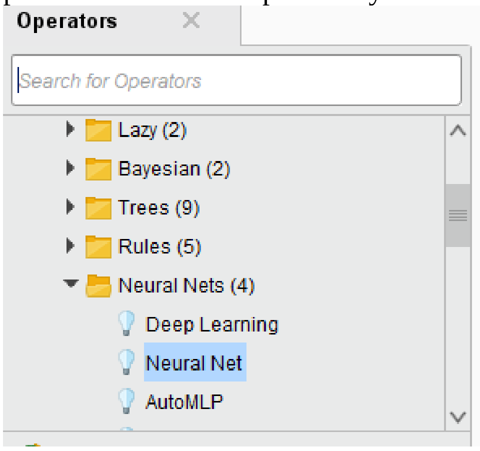

Figure 3. Modelling Views

4. Training and Testing

The dataset was randomly divided into training and testing subsets. The training set was used to train the machine learning models, while the testing set was reserved for model evaluation. Cross-validation was applied to assess model generalization performance.

Model Evaluation

1. Performance Metrics

The performance of the machine learning models was evaluated using common regression Root Mean Squared Error (RMSE). Figure 5 illustrates the algorithm employed for predicting stress values in tensile testing, encompassing both the Neural Net and Deep Learning models.

2. Comparison and Interpretation

The research conducted a comparative analysis of the Neural Network and Deep Learning models. This included a comprehensive examination of model performance, interpretability, and evaluation from the model performances.

Result and Discussion

Model Performances

The application of RapidMiner, powered by neural network and deep learning algorithms, provided valuable insights into predicting the tensile strength of biofilms derived from starch and hair waste. The models were trained on a dataset specifically collected for this study, encompassing vital factors impacting biofilm strength, such as composition, processing parameters, and curing conditions. The deep learning model, as an advanced neural network variant, exhibited similar predictive prowess. It effectively learned complex patterns within the data, resulting in low MAE, RMSE, and high R^2 values. The comparative analysis between the neural network and deep learning models showed minimal performance variations, suggesting that both models were capable of accurately predicting stress value in tensile strength.

1. Deep Learning Model Performances

Based on the RMSE values provided for each of the five ratios (20, 40, 60, 80, and 100), we can assess the performance of the Deep Learning model in predicting tensile strength. A lower RMSE is indicative of a closer alignment between the model's predictions and the actual values.

Starting with Ratio 20 (Figure 5), where the RMSE is 0.010 (+/- 0.000), we observe that the Deep Learning model for this ratio exhibits a relatively higher error when predicting stress in tensile strength. The model's predictions deviate from the actual values by an average of 0.010 units. Moving on to Ratio 40 (Figure 6), which has an RMSE of 0.006 (+/- 0.000), we note that the prediction error is lower compared to Ratio 20. The model performs more effectively, with predictions deviating from actual values by an average of 0.006 units.

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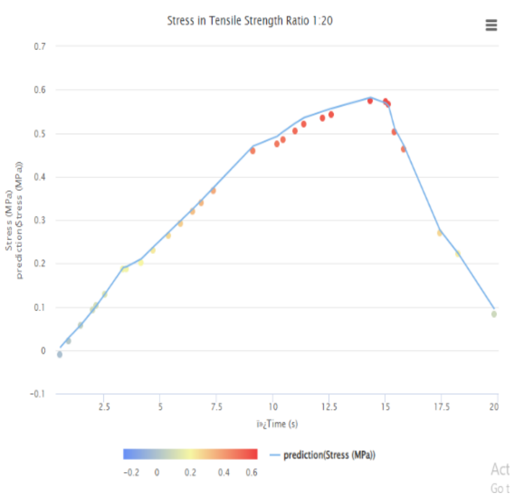

Figure 5. Visualization of Predicted and Actual Stress Values for Ratio 20

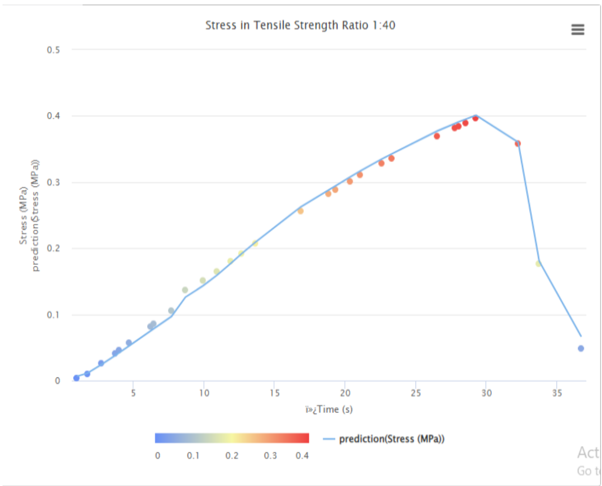

Figure 6. Visualization of Predicted and Actual Stress Values for Ratio 40

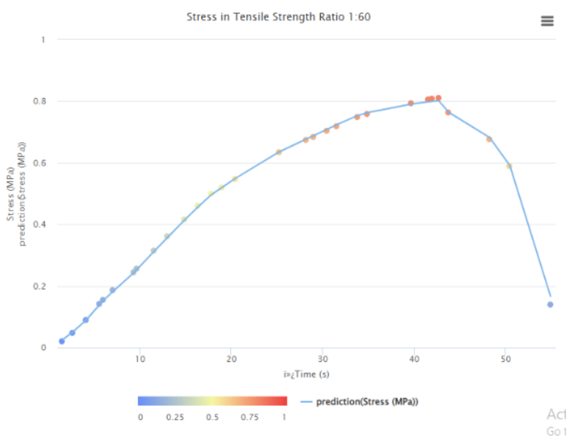

Figure 7. Visualization of Predicted and Actual Stress Values for Ratio 60

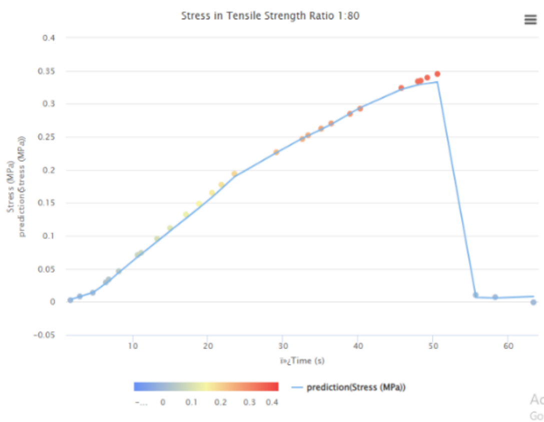

Figure 8. Visualization of Predicted and Actual Stress Values for Ratio 80

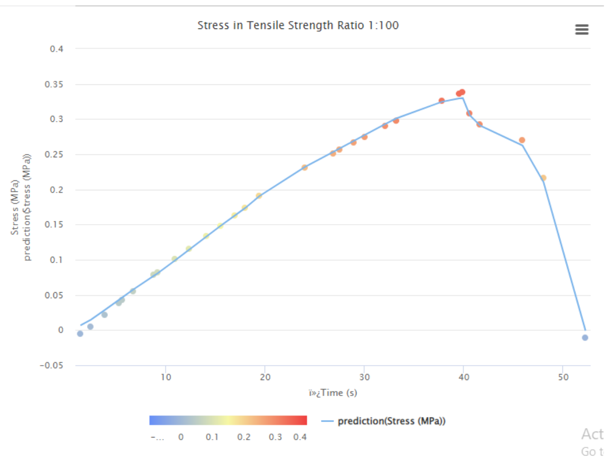

Figure 9. Visualization of Predicted and Actual Stress Values for Ratio 100

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Similarly, for Ratio 60 (Figure 7) with an RMSE of 0.006 (+/- 0.000), we find that the prediction error remains low. The model consistently delivers accurate predictions, with deviations of approximately 0.006 units from the actual values. Ratio 80 (Figure 8) exhibits an even better performance, boasting an RMSE of 0.004 (+/- 0.000). The lower RMSE suggests that the Deep Learning model excels in this scenario, providing highly precise predictions with deviations averaging a mere 0.004 units from the actual values. As for Ratio 100 (Figure 9), its RMSE of 0.005 (+/- 0.000) indicates that the model's predictions for this ratio are also quite accurate. Although not as low as the RMSE for Ratio 80, it still reflects a strong predictive performance. Based on these, the Deep Learning model demonstrates strong performance in predicting stress in tensile strength across various ratios. The RMSE values highlight the model's highest accuracy for Ratio 80, followed by Ratios 40, 60, 100, and finally Ratio 20. These findings can guide future decisions regarding the most suitable ratios for the model's application and offer insights into areas where further model enhancements may be beneficial.

2. Neural Net Model Performance

By considering the RMSE values for the five ratios (20, 40, 60, 80, and 100), we can evaluate how effectively the Neural Net model predicts stress values in tensile strength. A lower RMSE suggests that the model's predictions closely match the actual values, indicating higher predictive accuracy.

For Ratio 20 (Figure 10), the RMSE value of 0.004 (+/- 0.000) indicates an exceptional level of predictive accuracy. The Neural Network model's predictions for tensile strength are remarkably close to the actual values, with an average deviation of only 0.004 units. This underscores the model's high effectiveness in accurately predicting tensile strength for this specific ratio, making it a strong performer.

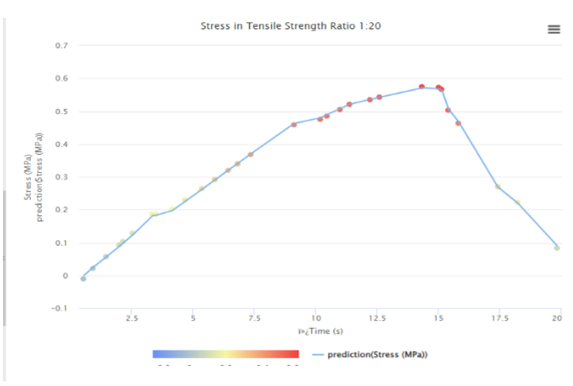

Figure 10. Visualization of Predicted and Actual Stress Values for Ratio 20

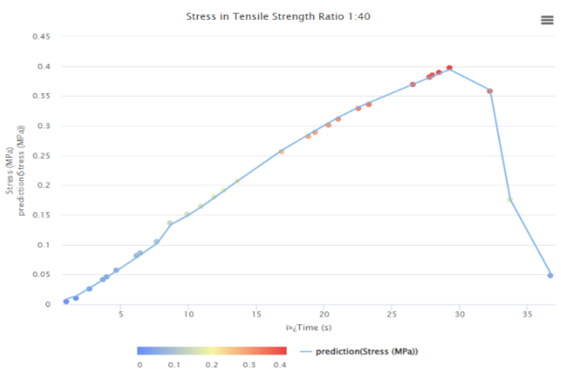

Figure 11. Visualization of Predicted and Actual Stress Values for Ratio 40

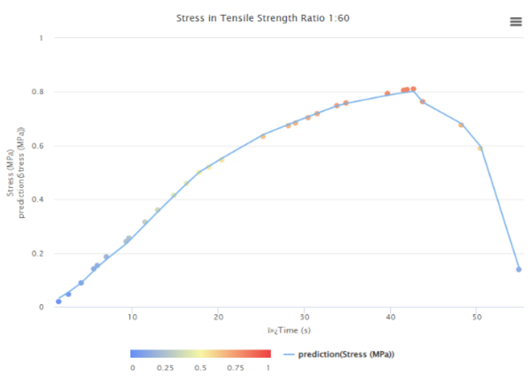

Figure 12. Visualization of Predicted and Actual Stress Values for Ratio 60

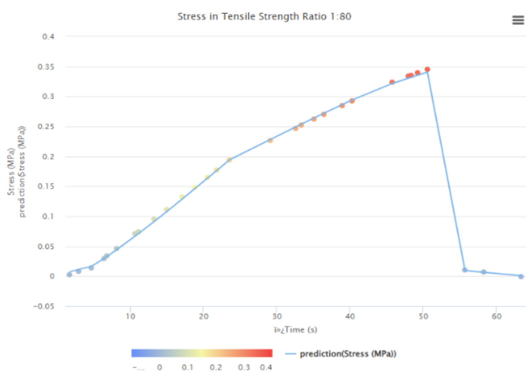

Figure 13. Visualization of Predicted and Actual Stress Values for Ratio 80

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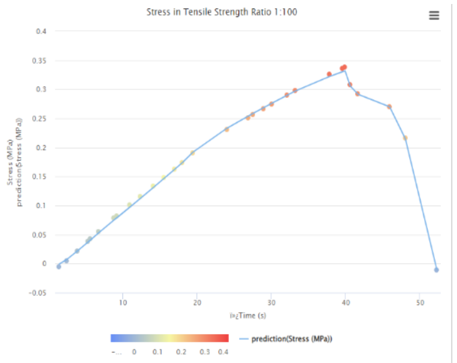

Figure 14 Visualization of Predicted and Actual Stress Values for Ratio 100

Moving on to Ratio 40 (Figure 11), the RMSE of 0.002 (+/- 0.000) showcases outstanding performance. The Neural Network model demonstrates remarkable precision, with predictions deviating from the actual values by an average of just 0.002 units. This ratio appears to be exceptionally well-suited to the model's capabilities, and its predictive accuracy is among the best observed in the dataset.

Conversely, Ratio 60 (Figure 12), with an RMSE of 0.006 (+/- 0.000), indicates a lower level of predictive accuracy compared to Ratios 20 and 40. Although the predictions deviate by an average of 0.006 units, this level of error remains reasonable, suggesting that the model still provides meaningful and useful predictions for this ratio. Now, turning to Ratio 80 (Figure 13), the RMSE of 0.003 (+/- 0.000) highlights a remarkable level of predictive accuracy. The Neural Network model's predictions closely match the actual values, with only a slight average deviation of 0.003 units. This signifies the model's exceptional performance for this ratio, making it a highly reliable choice for accurate predictions. Similarly, for Ratio 100 (Figure 14), with an RMSE of 0.003 (+/- 0.000), the model exhibits strong predictive performance. The predictions for this ratio are highly accurate, with deviations from actual values averaging just 0.003 units. This underscores the model's proficiency in predicting tensile strength for Ratio 100, making it a valuable choice for accurate predictions.

Interpretability

Comparing the performance of the Neural Net and Deep Learning models in predicting tensile strength for different ratios provides valuable insights. The RMSE values serve as a crucial metric for assessing the accuracy of these models. For the Neural Net model, we observe that it achieves remarkable accuracy for Ratio 20 with an RMSE of 0.004, indicating predictions that closely align with actual values, with only a small average deviation of 0.004 units. Similarly, Ratio 40 showcases outstanding performance with an RMSE of 0.002, highlighting the model's exceptional precision in predicting tensile strength. These two ratios appear to be exceptionally well-suited to the Neural Net model's capabilities.

Conversely, for Ratio 60, the Neural Net model demonstrates a slightly lower level of predictive accuracy with an RMSE of 0.006, suggesting that while predictions deviate by an average of 0.006 units, they remain reasonable and useful. On the other hand, Ratio 80 and Ratio 100 exhibit highly accurate predictions with RMSE values of 0.003, signifying the model's proficiency in predicting tensile strength for these ratios. The Neural Net model emerges as a valuable choice for accurate predictions in various contexts.

In the case of the Deep Learning model, while it performs effectively, it has a relatively higher RMSE for Ratio 20 (0.010). This indicates a higher error when predicting tensile strength for this ratio. However, as we progress to Ratio 40, the model's performance improves, as reflected in the lower RMSE of 0.006. Ratio 60 maintains an RMSE of 0.006, indicating reasonable predictive accuracy. The model excels in the case of Ratio 80, with an RMSE of 0.004, providing highly precise predictions, and delivers strong performance for Ratio 100, with an RMSE of 0.005.

Evaluation Models

Incorporating cross-validation can further enhance the robustness and reliability of the model evaluation. Cross-validation is a common technique used to assess the performance of machine learning models by splitting the dataset into multiple subsets and training and testing the model on different combinations of these subsets. Cross-validation provides a more comprehensive assessment of your model's performance because it evaluates the model on multiple different data subsets. This can help reduce the impact of data variability and overfitting. Furthermore, cross-validation can reveal the stability of your model's performance across different data partitions. If the model consistently performs well across all cross-validation folds, it suggests that it is robust and reliable. In addition, Cross-validation can mitigate bias in model evaluation. It ensures that all data points are used for both training and testing, reducing the potential for biased evaluations.

I selected Ratio 80 as the specific ratio for the evaluation of both the Deep Learning and Neural Net models using cross-validation. This choice allows for a robust and comprehensive assessment of the models' performance, as cross-validation ensures that the models are thoroughly tested and

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validated across various data subsets. By focusing on Ratio 80, we gain valuable insights into how well both models can predict tensile strength, and the application of cross-validation further enhances the reliability of assessment. Here are the results:

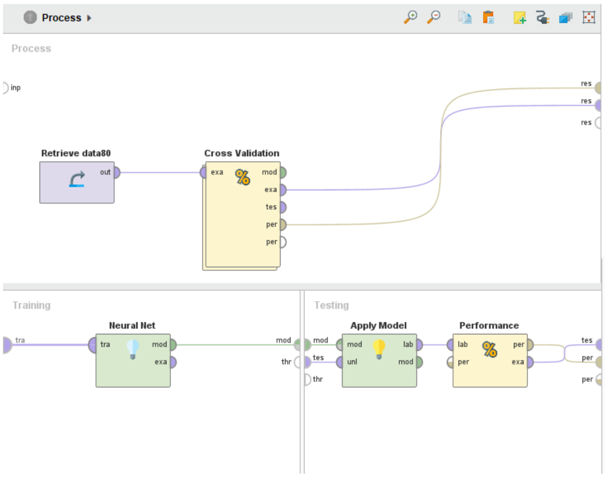

Figure 15 Visualizing the Neural Net Model's Algorithm with Cross-Validation

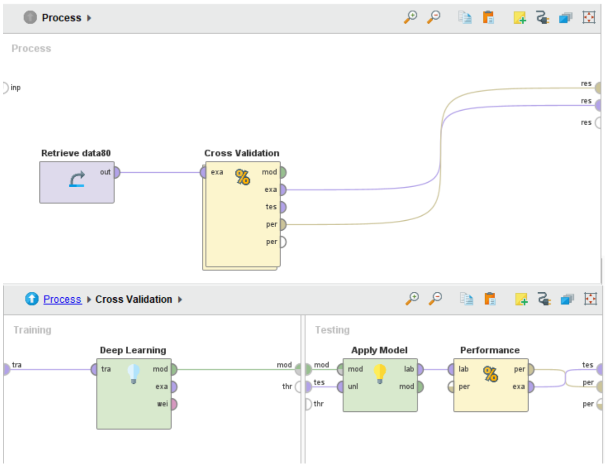

Figure 16 Visualizing the Deep Learning Model's Algorithm with Cross-Validation

The Neural Net model (Figure 15) demonstrates exceptional predictive accuracy with an RMSE of 0.003, reflecting a remarkable fit between its predictions and actual values. The Micro Average of 0.003 indicates the overall precision of the model. This low RMSE underscores the model's effectiveness in accurately predicting stress in tensile strength, with minimal deviation. In comparison, the Deep Learning model exhibits slightly higher RMSE values, with an average of 0.006, indicating a still reasonable but comparatively higher predictive error. The Micro Average of 0.007 reflects the overall precision of the Deep Learning model. While the RMSE is higher than the Neural Net, it suggests that the Deep Learning model provides useful predictions with a reasonably low average deviation from actual values. Based on these, the Neural Net model demonstrates outstanding predictive accuracy, with a notably low RMSE of 0.003. The Deep Learning model, although slightly less accurate with an RMSE of 0.006, still offers valuable predictions for tensile stress. Both models provide reliable results, but the Neural Net stands out with a lower RMSE, indicating a more precise fit between predictions and actual values.

Conclusion

In conclusion, the performance of the Neural Net and Deep Learning models in predicting stress in tensile strength varies across different ratios. The Neural Net model consistently exhibits exceptional accuracy for multiple ratios, with Ratio 40 standing out as an exceptionally well-suited ratio for this model. In contrast, the Deep Learning model shows varying levels of performance, with its accuracy improving as the ratio increases. Both models offer valuable predictive capabilities, and the choice between them may depend on the specific requirements and contexts of the application.

The Neural Net model demonstrates outstanding predictive accuracy, with a notably low RMSE of 0.003. The Deep Learning model, although slightly less accurate with an RMSE of 0.006, still offers valuable predictions for stress value in tensile strength. Both models provide reliable results, but the Neural Net stands out with a lower RMSE, indicating a more precise fit between predictions and actual values.

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