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Optimizing Degradable Plastic Density Prediction: A Coarse-to-Fine Deep Neural Network Approach

(Mengoptimumkan Ramalan Ketumpatan Plastik Terdegradasi: Pendekatan Rangkaian Neuron Dalam Carian Kasar-ke- Halus)

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ABSTRACT

Density is an important property for the production of high-quality degradable plastics. Density is useful to determine the type of plastic material and to detect physical changes in the plastic material. In this paper, a novel technique for predicting the density of degradable plastics using Deep Neural Networks (DNN) is presented. The aim was to reduce the dimension of the inputs in order to establish a strong relationship between the inputs using principal component analysis (PCA). The results show that the combination of polyethylene, oil palm biomass, starch and palm oil has a greater impact on predicting the density of degradable plastics. Subsequently, the number of hidden neurons is determined by a coarse-to-fine search to develop the network topology of the DNN model for predicting the density of degradable plastics. The developed DNN model consists of 4 input neurons, 62 neurons in the first hidden layer, 31 neurons in the second hidden layer and one output neuron. The developed DNN model showed high accuracy with the lowest values for RMSE, MAE and MSE, indicating that the use of a DNN model is a suitable method for predicting the density of degradable plastics. Furthermore, this study has the potential to make rapid and accurate predictions about the physical properties of degradable plastics in the context of polymers.

Keywords: Deep Neural Networks; degradable plastics; density

ABSTRAK

Ketumpatan adalah sifat penting untuk pengeluaran plastik terurai berkualiti tinggi. Ketumpatan berguna untuk menentukan jenis bahan plastik dan untuk mengesan perubahan fizikal dalam bahan plastik. Dalam kajian ini, teknik baharu untuk meramalkan ketumpatan plastik terurai menggunakan Rangkaian Neuron Dalam (DNN) dibentangkan. Matlamatnya adalah untuk mengurangkan dimensi input bagi mewujudkan hubungan yang kukuh antara input menggunakan analisis komponen utama (PCA). Keputusan menunjukkan bahawa gabungan polietilena, biojisim kelapa sawit, kanji dan minyak sawit mempunyai kesan yang lebih besar dalam meramalkan ketumpatan plastik terurai. Seterusnya, bilangan neuron tersembunyi ditentukan oleh carian kasar ke halus untuk membangunkan topologi rangkaian model DNN untuk meramalkan ketumpatan plastik terdegradasi. Model DNN yang dibangunkan terdiri daripada 4 neuron input, 62 neuron dalam lapisan tersembunyi pertama, 31 neuron dalam lapisan tersembunyi kedua dan satu neuron output. Model DNN yang dibangunkan menunjukkan ketepatan yang tinggi dengan nilai terendah untuk RMSE, MAE dan MSE, menunjukkan bahawa penggunaan model DNN adalah kaedah yang sesuai untuk meramalkan ketumpatan plastik terdegradasi. Selain itu, kajian ini berpotensi untuk membuat ramalan yang cepat dan tepat tentang sifat fizikal plastik terdegradasi dalam konteks polimer.

Kata kunci: Ketumpatan; plastik terdegradasi; Rangkaian Neuron Dalam

Introduction

The development of environmentally friendly plastics has increased due to public and research awareness of a green environment (Rosli, Wan Ishak & Ahmad 2021). Despite the excellent physical and mechanical properties of synthetic plastics, the cost of single-use plastics is high (Raja et al. 2022). Therefore, degradable plastics are chosen because they can be naturally degraded by living organisms (Salunke 2022).

Many experiments were invented for the development of degradable plastics. Among others, Zaman and Khan (2021) conducted an experiment with modified sago starch (SS) blended with low-density polyethylene (LDPE). The composites were tested for tensile strength and elongation at break. The experiment showed that the treated SS composites exhibited a decrease in tensile strength but an increase in elongation at break compared to untreated SS plastic composites. Dugvekar and Dixit (2021) developed an experiment on the tensile strength, flexural strength and impact strength of recycled high-density polyethylene (HDPE) composites reinforced with jute fibers and rice stalk dust. The study found that the combination of recycled HDPE, jute fibers, and rice stalk gave better results in tensile strength, flexural strength and impact strength of the composites. According to their findings, jute fibers and rice stalk dust can replace natural wood fibers. Zaman and Beg (2021) investigate different types of starch (sago starch, corn starch, potato starch, tapioca starch and wheat starch) reinforced with LDPE. This study focuses on the tensile strength, elongation at break, impact strength and tensile modulus of the composites. The experimental results showed that the combination of LDPE and sago starch has the best mechanical properties compared to other types of starch. The existing literature focuses on the mechanical properties of degradable plastics, including factors such as tensile strength, tensile modulus, flexural strength and impact strength. However, the physical properties of degradable plastics have only been researched to a limited extent, leaving a knowledge gap between the mechanical and physical properties of degradable plastics. Therefore, the aim of this study was to close this gap by investigating the physical properties of degradable plastics, especially the density.

The Deep Neural Networks (DNN) are machine learning based artificial neural networks used for classification, clustering and prediction. The general architecture used to build DNN models are feed-forward neural networks consisting of many hidden layers. The DNN together with principal component analysis (PCA) are used to predict the density of degradable plastics. In general, the number of hidden neurons in the hidden layer of a DNN model is determined by researchers through trial and error (Shin-Ike 2010).

Previous studies have shown that when predicting the physical and mechanical properties of degradable plastics using an artificial neural network (ANN), a trial-and-error method is typically used to determine the best number of hidden neurons. In this method, the best number of hidden neurons is selected based on the lowest mean square error (MSE) and root mean square error (RMSE) values. Mairpady, Mourad and Mozumder (2021) used a feedforward approach for a neural network to determine the number of hidden neurons based on the values of coefficient of determination (R^2) band MSE. They concluded that the constructed ANN indeed provides optimal prediction results with minimal errors. However, they pointed out that the trial-and-error procedure can be tedious, costly and occasionally unreliable. In Khan et al. (2019)' study, the mean absolute error (MAE) values were all within acceptable limits and amounted to less than 5%. This led to the conclusion that ANNs are a potential tool for accurate predictions. Leong et al. (2018) experimented with varying the number of hidden neurons in the range of 1 to 30, and found that the optimal number of hidden neurons was 30, as it yielded the lowest MSE and RMSE values, with R^2 values close to one. Based on these results, they concluded that feedforward neural networks have the potential to simulate the synthesis process of polyhydroxyalkanoates without the need for experimental work.

While the trial-and-error method has shown effective performance in estimating the number of hidden neurons in a previous study, an alternative method was used in this study when developing the DNN model to predict the density of degradable plastics. The reason for this decision was concerns about the lengthy, expensive and occasionally unreliable nature of the trial-and-error method.

The coarse-to-fine search technique is the alternative method for determining the optimal number of hidden neurons for multilayer perceptron networks. The advantages of the coarse-to-fine search technique are that this technique does not rely on trial and error, is less time consuming as the number of hidden neurons is selected based on the lowest MSE, and is more accurate. Examples of studies include, Jahedsaravani, Marhaban and Massinaei (2014), who investigated the optimal structure of a feed-forward neural network (NN) using a coarse-to-fine search technique to predict the buoyancy of a copper sulfide output from images. The best number of hidden neurons in this study consists of four neurons in the input layer, eight neurons in the hidden layer, and one neuron in the output layer. The developed NN model has been successfully applied in the field of control systems. In another study, Jahedsaravani, Marhaban and Massinaei (2016) applied the coarse-to-fine search technique in a simulation of metallurgical performance. By applying the

coarse-to-fine search technique, they found that the best number of hidden neurons is five neurons in the input layer, eight neurons in the hidden layer, and one neuron in the output layer. The results show that the developed NN is efficient in predicting a metallurgical parameter. Narine, Popescu and Malambo (2019) investigated the effect of multiple hidden neurons in neural networks to predict the aboveground biomass of forests. The study compared the techniques proposed by Huang (2003) with those of Doukim, Dargham and Chekima (2010). They found that the technique proposed by Doukim, Dargham and Chekima (2010) did not perform satisfactorily compared to the technique proposed by Huang (2003).

The main aim of this study was to establish a strong correlation between the inputs. To achieve this, PCA was used to reduce the dimensionality of the inputs. The second objective was to determine the optimal number of hidden neurons in the network topology using a coarse-to-fine search technique. Finally, the developed DNN model was used to predict the density of degradable plastics.

Materials and Methods

Data collection

The used data in this study collected from the Malaysian Palm Oil Board (MPOB). The MPOB experts were responsible for formulating the degradable plastics and conducting experiments to evaluate their physical properties. An expert from MPOB determined the input and output factors based on laboratory experiments. The inputs include the percentage of polyethylene (PE), oil palm biomass (OPB), palm oil (PO) and starch, while the output is the density (gcm^{-3}) of the degradable plastics.

Configuration of deep neural networks

Figure 1 shows the steps to develop the proposed DNN model and its performance test. As shown in Figure 1, the research framework is divided into three main phases. The first phase is the pre-processing of the data. The original data consists of only 22 samples. To solve this problem, the nonparametric bootstrapping technique invented by Bradley Efron in 1979 was used. The bootstrapping technique has been empirically applied in the plastics industry and other sectors (Gimenez-Nadal, Molina & Velilla 2019; Leong et al. 2018). Bootstrapping is a technique in which the original data is repeatedly replaced by new data.

For this study, Let $X = x_1, x_2, ..., x_n$ be a sample of size n = 22. A new sample is generated by a repeated sample X with replacement, denoted by $X^{*b} = x_1^{*b}, x_2^{*b}, ..., x_n^{*b}$ where b is the b^{th} bootstrap sample, b = 10. A new sample consists of repeated values from the original and some values may occur once. After bootstrapping, the new dataset consists of 220 samples.

The next step in the pre-processing method is to reduce the number of inputs using PCA. The successful use of DNN together with PCA has recently been observed in many domains (Azman et al. 2022). Our previous research (Bakar et al. 2023), has extensively covered the detailed process of PCA computation. In this study, the PCA method was used to determine the best composition for 2-inputs, 3-inputs, and 4-inputs in predicting the density of degradable plastics.

In the second phase, referred to as DNN model development, the split ratio of the data sets is examined. Shahin, Maier and Jaksa (2000) found that there is no obvious correlation with this ratio. In contrast, Muraina (2022) highlighted that the ratio between the data can have an impact on the performance of the model, but that there is no standard ratio. Researchers usually divide the data into 90%: 10%, 80%: 20% or 70%: 30%. In this study, the data set is divided into a training data set and a test data set, with a ratio of 70%: 30% for training and test, respectively. Nguyen et al. (2021) have shown that this ratio is particularly effective in influencing the accuracy of the DNN model. This is attributed to the fact that the training dataset enables efficient mapping of inputs, resulting in high-quality outputs. At the same time, the test dataset effectively evaluates the performance of the model.

In general, the network is trained with a randomly searched architecture. The error decreases after a few training epochs and the training algorithm terminates when the test error increases after several iterations of the sequence or when the limits of the maximum error per epoch are exceeded (Mohammadi et al. 2020). In contrast, when implementing the early stopping method, the error of the test data set will exceed that of the training data set, the training process will be stopped and the network weights associated with the minimum test error will be implemented (Mohammadi et al. 2020). According to Etim (2022), the application of the early stop method improves the ability of the ANN model to generalize effectively. Furthermore, the implementation of the early stopping method in ANN is essential. The reason for this is to identify important connections in the early stages of training. Another reason for choosing the early stopping method is its effectiveness in addressing the problem of overfitting (Liang et al. 2019). In this study, the dataset is trained with the early stopping method for 4-inputs, 3-inputs and 2-inputs. The last phase is the evaluation of the model. In this final phase, the predictive ability of the DNN models is evaluated using the RMSE, MSE, and MAE.

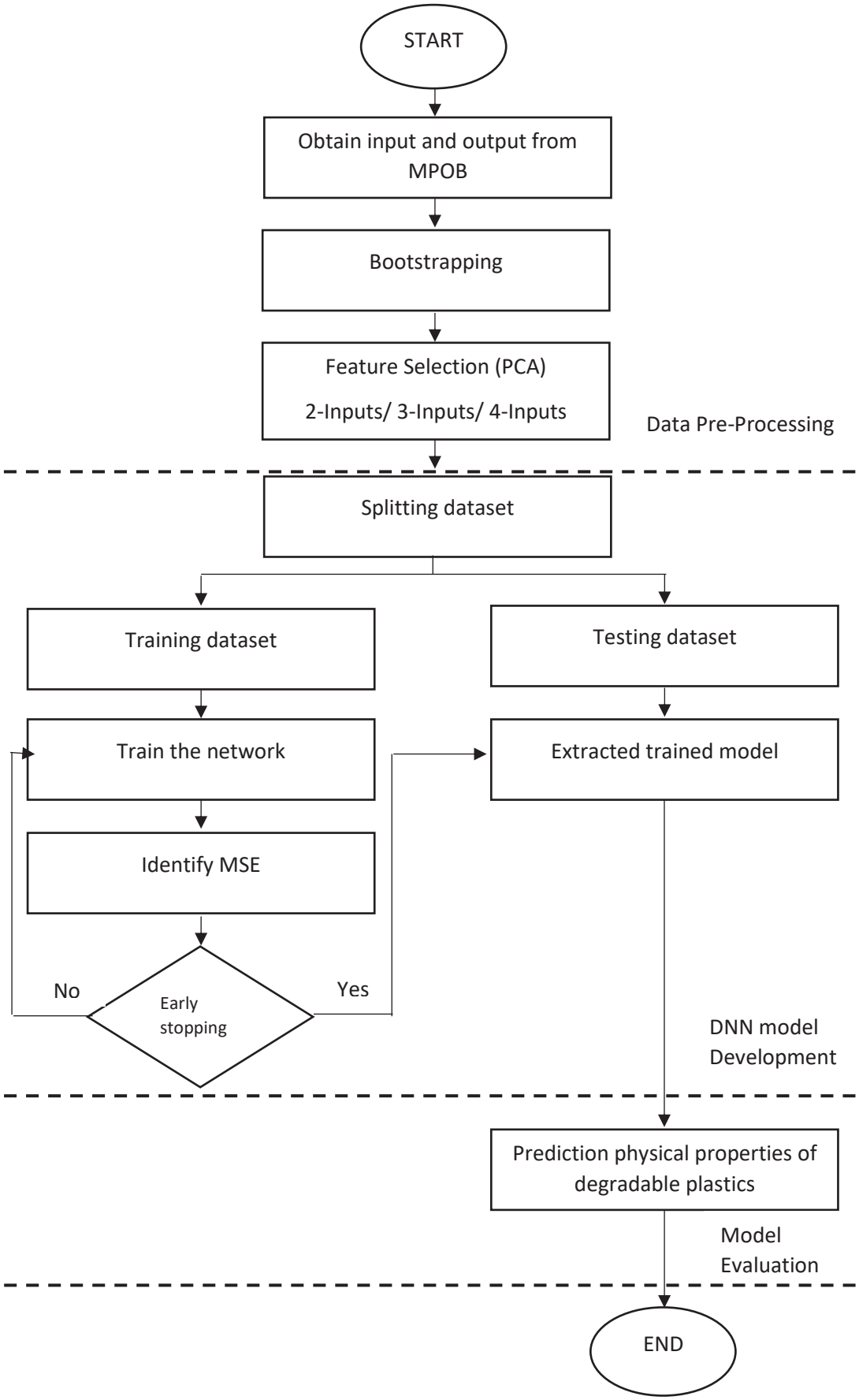

FIGURE 1. Research framework for predicting the density of degradable plastics using DNN

DATA PRE-PROCESSING

Since the sample obtained from the MPOB laboratories for use in the DNN model is small. And according to Khaki and Wang (2019), the larger the dataset, the more accurate the prediction. Therefore, the bootstrapping method is used in this study to resample the original data. The next step is feature selection to select the best input variables for 2-inputs, 3-inputs and 4-inputs variables using PCA. In this study, PCA is performed in Jupyter Notebook software version 6.3.0 with Tensorflow Anaconda package.

DEVELOPMENT OF THE DNN MODEL

This research employs a two hidden layer multilayer perceptron (MLP) neural network. One of the biggest challenges in developing MLP neural network is to determine the optimal number of neurons of the hidden layer based on a set of training patterns. It is very important to determine the optimal number of neurons in the hidden layer. A large number of neurons in the hidden layer can lead to overtraining, resulting in a progressive increase in the weight of the hidden layer neurons and reducing the generalization ability of the system. On the other hand, using too few neurons can lead to insufficient training.

To address this problem, a novel technique known as coarse-to-fine search technique, introduced by Doukim, Dargham and Chekima (2010) for predicting the density of degradable plastics, is used in this study. Coarse-to-fine search technique involves two steps. First, the number of hidden neurons in the first hidden layer (HN1) is determined using the binary search mode. The tested values for HN1 include 4, 8, 16, 32, 64, and 128. To avoid long training times, the maximum number of HN1 is set to 128. The number of hidden neurons in the second hidden layer (HN2) is set to half the number of HN1.

The following discussion of the structure of a neural network uses four neurons in the input layer and one neuron in the output layer. The neural network structure used in this study follows a 4-[HN1-HN2]-1 configuration. Consequently, the network structures were specified as 4-[4-2]-1, 4-[8-4]-1, 4-[16-8]-1, 4-[32-16]-1, 4-[64-32]-1, and 4-[128-64]-1, as shown in Figure 2. Six networks were trained and their MSE values were calculated and documented. The network structure with the lowest MSE value was selected. Figure 2 shows that the network structure 4-[64-32]-1 yielded the lowest MSE value of 0.00003, leading to the selection of HN1=64.

The second step is to determine the optimal number of hidden neurons for the hidden layers. This is done by a sequential search within a fixed range based on the network structure determined in the first step. According to the approach of Doukim et al. (2011), the fixed range of sequential search begins from $HN_{BL} + [(1/2) \times (HN_B - HN_{BL})]$ to $HN_B + [(1/2) \times (HN_{BH} - HN_B)]$ when HN1 is equal to 4, 8, 16, 32 or 64. HN_B is the chosen HN1, HN_{BL} is the nearest lower value of HN_B, and HN_{BH} is the nearest upper value of HN_B. Figure 2 shows that HN1 is 64. Thus, HN_B equals to 64, HN_{BL} and HN_{BH} are 32 and 128, respectively. The fixed range for the sequential search is from HN1=48 to HN1=96. Table 1 presents the sequential search outlined in step 2, starting with a network structure of 4-[48-24]-1 and progressing to 4-[96-48]-1.The network structure with the smallest MSE is selected.

In this study, the DNN model consists of an input layer, two hidden layers and an output layer. The input layer consists of four nodes, while the number of neurons in the hidden layers is determined using a coarse-to-fine search technique. The output layer consists of a single node and these layers are interconnected. The DNN architecture is illustrated in Figure 4.

$$\text{Input layer: Let input vector } = x_i^m \tag{1}$$

The associated weights initialized by the network designer are multiplied by the input values. The new weights are passed to the hidden layer.

Hidden layer: The new weights received from the input layer then convert a given value into the network's output error function.

Each hidden neuron has an associated activation function. The weighted sum it receives from the previous layer is the input. The output of this function is the weighted input of the next hidden layer to the output layer. In this study, the rectified linear unit (ReLU) activation function was used. The ReLU activation function is described as follows:

$$\begin{aligned} f(x) &= 0; \; for \; x < 0 \\ f(x) &= x; \; for \; x \geq 0 \end{aligned} \tag{2}$$

The Adam optimization algorithm was used in training the model. Mean squared error (MSE) was used as the loss function and mean absolute error in percent (MAPE) as the metric function. The best iteration was determined based on the MSE values.

$$\mathrm{MSE} = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} \left(y - \hat{y}\right)^2 \quad (3)$$

where y is the output of the test dataset; and $\hat{y}$ is the predicted output. The error is reduced by changing the weights according to the following equation:

$$\Delta \mathrm{w}_{\mathrm{ij}}^{\mathrm{n}} = -\eta \frac{\partial MSE}{\partial \mathrm{w}_{\mathrm{ij}}^{\mathrm{n}}} \quad (4)$$

where n is the learning rate.

In the feed-forward method, the input nodes receive a flow of data from the input layer to the output layer. The weights of the network were updated using the backpropagation algorithm to more accurately map the input to a desired output while minimizing MSE.

Output Layer: Output = activation (dot(input, kernal) + bias

$$\mathrm{y}_{\mathrm{j}}^{\mathrm{m+1}} = \vartheta\left(\sum_{i=1}^{m} w_{ij}^{n}\, x_i^m\right) + b_{ij} \quad (5)$$

The linear activation function was used in the construction of the output layer.

$$\mathrm{f}(\mathrm{x}) = x \quad (6)$$

Figure 5 shows the connection between input values and output value. The DNN model was created using the Jupyter Notebook software version 6.3.0 and the Tensorflow Anaconda package with the Python programming language version 3.7.0.

MODEL EVALUATION

The predictive performance of the DNN model is measured by comparing the predicted values with the actual values of the laboratory results. The error is calculated using RMSE, MSE and MAE.

The Root Mean Square Error (RMSE) is a good measure of accuracy, but only for comparing the prediction errors of different models as it is scale dependent. RMSE measures how accurately a model predicts the target. An RMSE value closer to 0 means a better fit. The formula for the RMSE is as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{t=1}^{N} \left(A_t - F_t\right)^2} \quad (7)$$

where A_t and F_t are the actual and fitted values, respectively; and N is the number of training and test samples, respectively (Popoola et al. 2019).

The mean square error (MSE) measures the mean value of the squared error. The MSE is used to check how close the predicted values are to the actual values. The lower the MSE, the closer the prediction is to reality.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \quad (8)$$

where y_i are the predicted values and $\hat{y}_i$ are the actual values (Popoola et al. 2019).

The mean absolute error (MAE) is used to evaluate the predicted value based on the predicted errors. The predicted error is defined as actual values minus predicted values. The mean percentage error is the average of all percentage errors. The formula of MAE is as follows:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \left|y_i - x_i\right|}{n} \quad (9)$$

where y_i is the prediction; and x_i is the actual value (Swamidass 2000).

RESULTS AND DISCUSSION

The first aim of this study was to reduce the dimension of the inputs using PCA. Table 2 shows the comparison of the loss function and metrics on different principal components for 4-inputs, 3-inputs and 2-inputs. The data in Table 2 shows that a 4-inputs combination (PE/OPB/Starch/PO) yields the smallest MSE loss function value, 0.000030, followed closely by 3-inputs combination (PE/OPB/Starch) with a value of 0.000179, (PE/OPB/PO) with 0.000225, and 2-inputs (PE/OPB) with 0.000342. A lower MSE loss function and MAPE value indicate a more effective model. Analysis of the MAPE metric shows that the 4-inputs combination has the lowest percentage error, followed by 3-inputs and 2-inputs. When predicting the density of degradable plastics, the 4-inputs combination performs better than the 3-inputs and 2-inputs combination in terms of the lowest MSE and MAPE. It can be seen that the results do not lead to a reduction in the number of inputs. Nevertheless, the use of PCA has proven to be beneficial as it shows a robust relationship between the inputs for predicting the density of degradable plastics.

TABLE 1. The range of sequential search

NETWORK STRUCTURE	MSE
4-48-24-1	0.000030
4-49-25-1	0.000047
4-50-25-1	0.000172
4-51-26-1	0.000064
4-52-26-1	0.000135
4-53-27-1	0.000037
4-54-27-1	0.000547
4-55-28-1	0.000071
4-56-28-1	0.000039
4-57-29-1	0.000073
4-58-29-1	0.000755
4-59-30-1	0.000030
4-60-30-1	0.000042
4-61-31-1	0.000031
4-62-31-1	**0.000029**
4-63-32-1	0.000032
4-64-32-1	0.000175
4-65-33-1	0.000034
4-66-33-1	0.000034
4-67-34-1	0.000108
4-68-34-1	0.000055
4-69-35-1	0.000394
4-70-35-1	0.000037
4-71-36-1	0.000031
4-72-36-1	0.000031
4-73-37-1	0.000030
4-74-37-1	0.000325
4-75-38-1	0.000048
4-76-38-1	0.000046
4-77-39-1	0.000085
4-78-39-1	0.000043
4-79-40-1	0.000032
4-80-40-1	0.000137
4-81-41-1	0.000031
4-82-41-1	0.000052
4-83-42-1	0.000030
4-84-42-1	0.000030
4-85-43-1	0.000130
4-86-43-1	0.000030
4-87-44-1	0.000030
4-88-44-1	0.000092
4-89-45-1	0.000033
4-90-45-1	0.000052
4-91-46-1	0.000029
4-92-46-1	0.000043
4-93-47-1	0.000039
4-94-47-1	0.000038
4-95-48-1	0.000031
4-96-48-1	0.000036

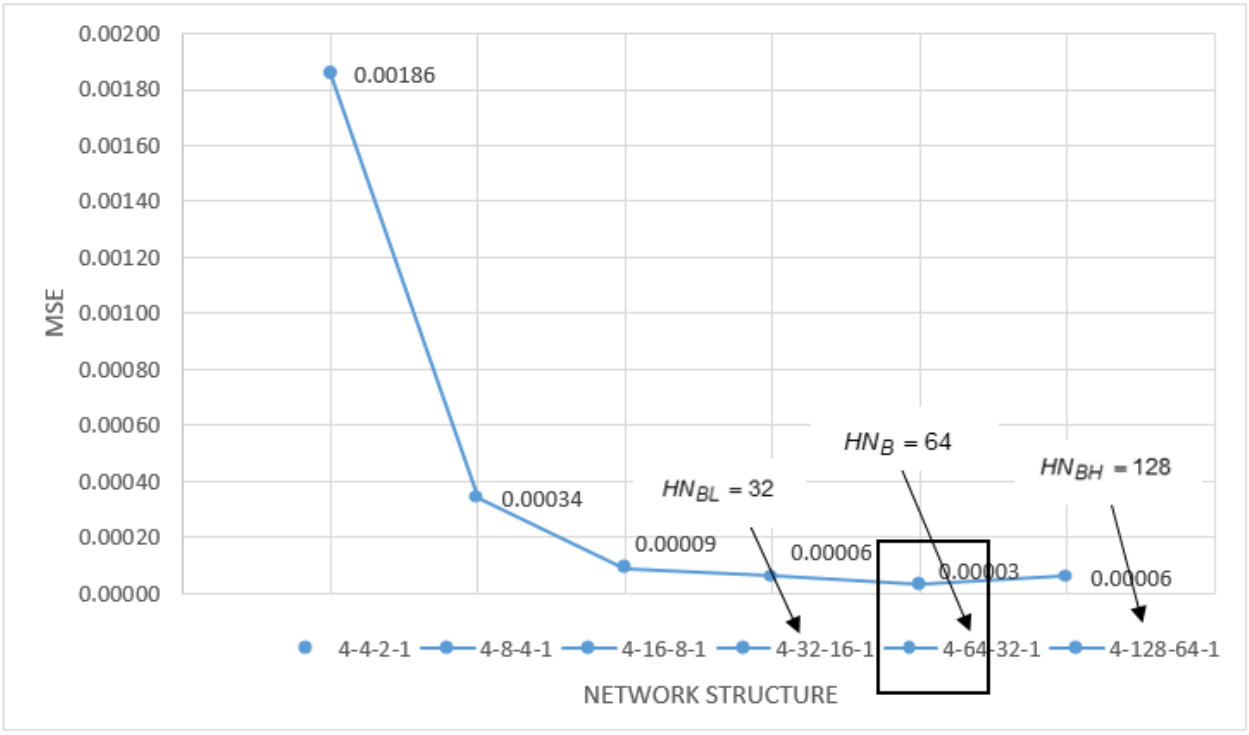

FIGURE 2. Coarse binary search

Figure 6(a) and 6(b) shows the results of the loss and metric functions for the 4-input DNN model for both training and testing. In both figures, the curves for training and testing are close to each other and show no signs of overfitting or underfitting. The results of the sequential search are shown in Figure 3. It shows that the MSE results initially vary for different HN1 values until the minimum MSE value of 0.000029 is reached. The optimal lowest HN1 value associated with the lowest MSE is HN1=62. Consequently, the established network structure consists of 4 input neurons, 62 neurons in the first hidden layer, 31 neurons in the second hidden layer, and an output neuron labelled 4-[62-31]-1. The proposed technique proves to be more efficient in terms of training time as it involves a course-to-fine search strategy that combines binary search with sequential search. This approach differs from previous work on predicting the mechanical properties of degradable plastics, which relied solely on sequential search (Khan et al. 2019; Leong et al. 2018; Mairpady, Mourad & Mozumder 2021). It is notable that the MAE error of the model is smaller than in published work such as Mairpady, Mourad and Mozumder (2021), suggesting that the course-to-fine technique is more accurate. Furthermore, these results may have been influenced by the ratio of the training and test datasets. This study has shown that the 70%:30% split of training and test dataset is appropriate for training and testing the DNN model. This result is consistent with other published work, such as Nguyen et al. (2021), who investigated different ratios of training and test datasets for different machine learning models (Artificial Neural Network, Extreme Learning Machine and Boosting Trees algorithms). The use of the early termination method may also have affected the developed DNN model. By using early termination, the developed DNN model uses only 29 epochs. Other studies and research have also confirmed that the early termination method improves the ability of the ANN model to generalize effectively (Etim 2022; Liang et al. 2019; Mohammadi et al. 2020).

The third objective of this study was to predict the density of degradable plastics using the DNN model. The RMSE, MAE and MSE values for predicting density based on 4-inputs to the DNN model are shown in Table 3. The calculated RMSE, MAE, and MSE error values are 0.00551, 0.002164, and 0.000030, respectively. The small RMSE values indicate equally high prediction accuracy for predicting density based on 4 input variables. In addition, the low MAE and MSE values of the DNN model indicate that its performance

in predicting the density of degradable plastics based on 4 input variables is more reliable and credible. It is assumed that the resampling dataset is one of the reasons for the excellent results. By providing the DNN model with a large dataset, the network was able to successfully achieve good generalization.

In summary, the results show that the developed DNN together with PCA effectively models the complicated relationship between the input and output variables. Furthermore, the performance measurement of the RMSE, MAE, and MSE error values shows that the application of the coarse-finding technique in the construction of the DNN model successfully predicts the density of degradable plastics with minimal errors in the training dataset. Nevertheless, some limitations were identified in this study. The size of the dataset and the number of variables are relatively small, and the learning capacity of the DNN is limited to the application of a coarse-to-fine search technique.

TABLE 2. Comparison of loss function and metrics on different principal components

Number of PC	Component	Loss (MSE)	Metrics (MAPE)(%)
4	PE/OPB/Starch/PO	0.000030	0.24
3	PE/OPB/Starch	0.000179	1.05
3	PE/OPB/PO	0.000225	1.06
2	PE/OPB	0.000342	1.64

TABLE 3. RMSE, MAE and MSE values of predicted density of degradable plastics

RMSE	MAE	MSE
0.005506	0.002164	0.000030

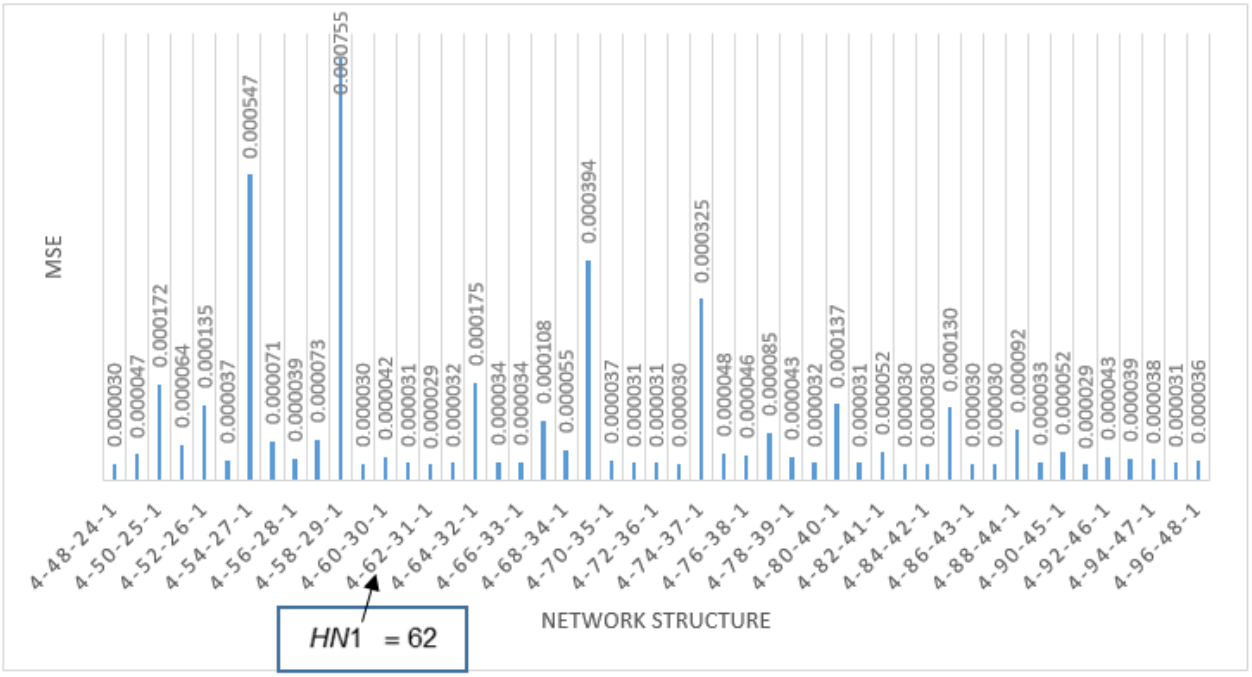

FIGURE 3. Sequential search

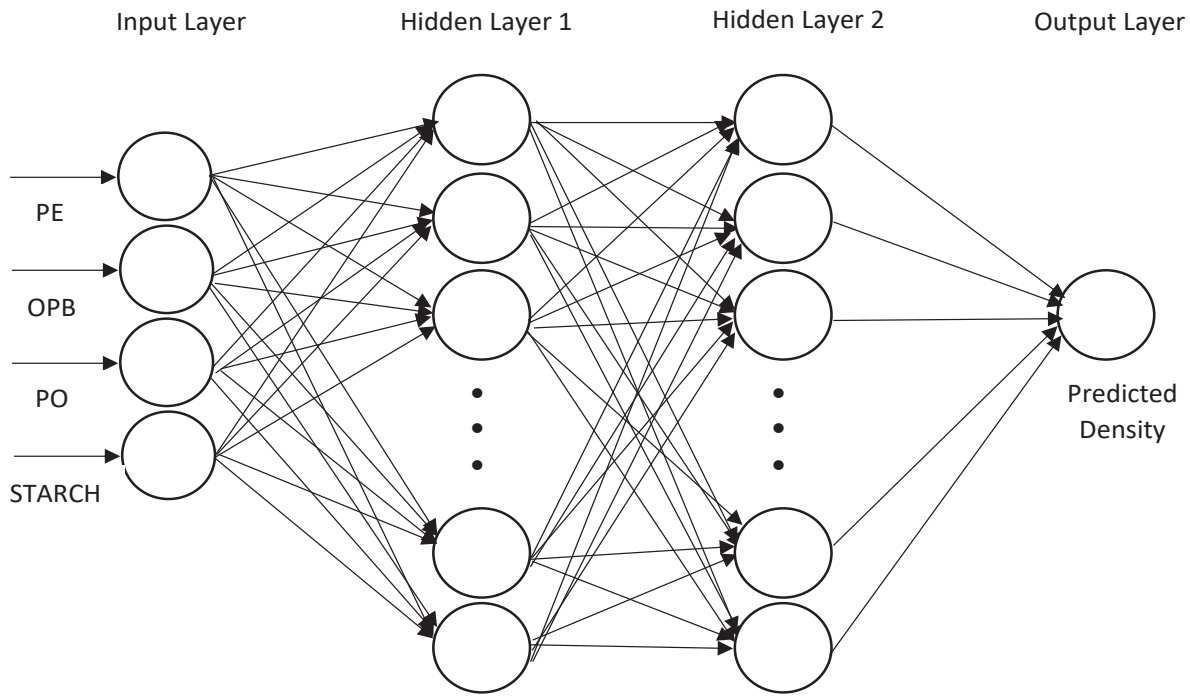

FIGURE 4. Layered structure of the DNN model for predicting the density of degradable plastics

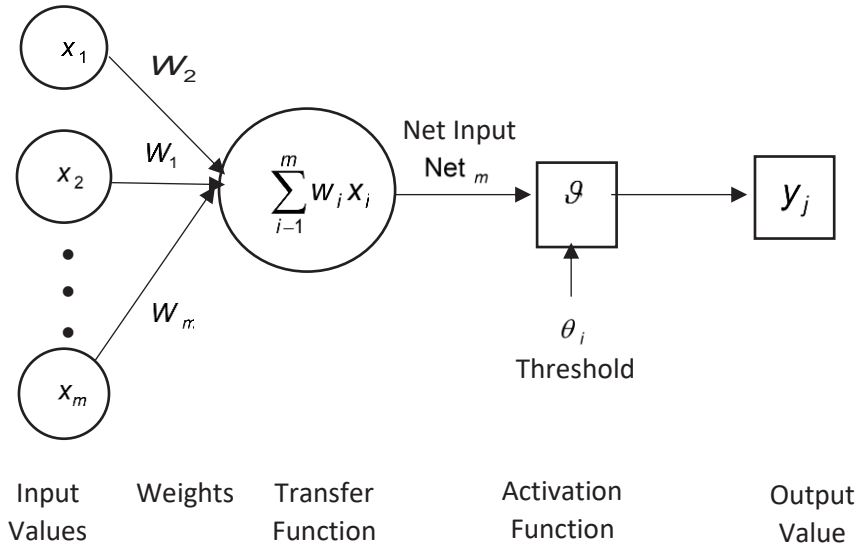

FIGURE 5. Connection between input values and output value

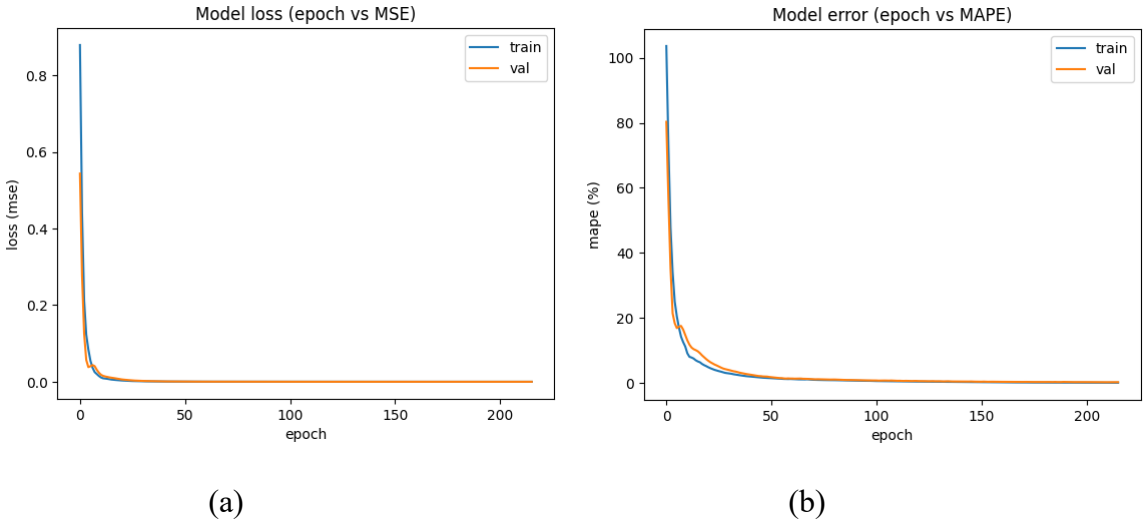

FIGURE 6. a) 4-inputs of the loss function versus the number of epochs, and b) 4-inputs of the MAPE compared to the number of epochs

CONCLUSIONS

Biodegradable plastics can reduce plastic waste if the degradable plastic product can break down into small pieces within a certain time. Density plays a role in the production of a good degradable plastic, as changes in density affect some of the mechanical properties of degradable plastics, such as tensile strength. Therefore, a novel method for predicting the density of degradable plastics using DNN was presented in this study. Feature selection using the PCA approach successfully found the best features for predicting the density of degradable plastics. The PCA results show that the best combination of inputs for predicting the density of degradable plastics is PE/OPB/Starch/PO.

In the development of the DNN topology, the number of neurons in the input and output is determined by the number of parameters. However, the problem is to find the number of hidden neurons in the hidden layer. Therefore, in this study, we proposed a coarse-to-fine search technique to determine the number of hidden neurons in the development of DNN topology and predict the degradable plastic density. There are numerous advantages associated with this technique. One of the advantages is the potential reduction in training time required to find the optimal number of neurons without compromising the accuracy of the model. The applicability of this technique goes beyond image analysis and prediction and extends to various real-world problems. Moreover, high accuracy can be achieved by implementing this technique. The DNN model has also successfully predicted density with high accuracy, with the lowest values of RMSE, MSE and MAE.

In the current study, we only considered the DNN model for predicting the density of degradable plastics with a different number of input values (4-inputs, 3-inputs, and 2-inputs). In the future, the performance of the DNN model will be compared with the other models, which may affect the determination of input values and prediction accuracy. In addition, the significance of this study lies in its significant contribution to improving the learning ability of the DNN model by applying the coarse-to-fine search technique. This DNN model was developed to minimize errors and improve the stability of the network in predictions in the field of polymer science. The learning ability and learning algorithm of the DNN could be explored in future research by investigating different approaches to modeling the physical properties of degradable plastics and then comparing their effectiveness. It is also important to consider the physical properties, as they significantly influence the mechanical properties of high-quality degradable plastics.

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