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Comparison of KNN and DNN Classifiers Performance in Predicting Mobile Phone Price Ranges

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Abstract

The aim of this study was to compare the classification performances of K-nearest neighbors (KNN) and Deep Neural Networks (DNN) models in a dataset. For this purpose, the "mobile price forecast" dataset has been selected. It includes 20 different features of mobile phones such as battery power, Bluetooth function, memory capacity, screen size. The problem presented in the dataset is to determine the price range class before the mobile phones are released. Such a forecast will help companies that manufacture mobile devices to estimate the price of their mobile phones in a more convenient method to compete against their competitors in the market. In the implementation phase of the study, the KNN and DNN models were created in Python 3.6 with the Sklearn and Keras libraries. The classification performances of the models were determined using F-1 score, precision, recall and accuracy measurements. As a result of the study, validation data was classified with 92% accuracy using the trained DNN model. In addition, at another stage of the study, the price range for 1000 devices with different features was determined by using a test dataset that was not labeled, and the results produced by both models were compared.

Keywords: *Classification; Deep Neural Networks; KNN; Mobile Phone Prices.*

1. Introduction

In recent years, data classification applications have spread too many areas such as image processing [1], natural language processing [2], energy optimization [3], medical science [4], risk analysis [5] and macro-economic forecasts [6]. The main purpose of the classification process is to predict what an image is, or to determine what the available data means in a data set with a large number of different categories of data. At the base of the algorithms developed for this purpose is the training of the models by using training data, and then the classification of new data through these trained models.

Examples of machine learning-based algorithms include logistic regression (LR), Support Vector Machine (SVM), K-nearest neighbor (KNN), Random Forest (RF), and artificial neuron networks (YSA). The classification performances of these algorithms on various data sets have been studied in many studies in the literature. Some of them are based on comparing newly developed algorithms with existing algorithms, while some are studies in which different algorithms are evaluated by comparing different datasets. Pondhu and Kummari [7] used machine learning techniques in the process of gender classification in their work. As a result of the study, they showed that Ann performed better than SVM with its well-adjusted parameters. A study on text classification was conducted by Aydogan and Karci in 2019 [8]. In the study, it was stated that SVM performed better in the classification of Turkish texts than in Naive Bayes.

The KNN algorithm is also one of the simplest and most widely used classification algorithms in machine learning algorithms. The KNN algorithm conforms to the multiclass tag classification problem and has a good generalization ability [1]. KNN algorithm is a lazy algorithm and works as an ideal estimator that memorizes data perfectly [9]. Looking at examples of applications of the KNN algorithm in the literature, it can be seen that it applies to the problem of image classification [1], text classification [10], file classification [11] and classification of epilepsy from EEG signals [12].

On the other hand, Deep Neural Network (DNN) has been become a machine learning method that has been mentioned very rapidly in data classification recently. The DNN is a model of neural networks in which the number of layers in artificial neural networks increases and becomes deeper and wider [13]. The processing speeds of DNN have considerably increased thanks to the Graphics Processor Unit (GPU) performing the vector and matrix operations very quickly. DNN algorithm has been applied to classification problems in almost all areas in the literature for example the classification of fungal species [13], acoustic scene classification [14] and classification of Alzheimer's disease [4].

It has been shown in these studies that KNN and DNN algorithms are successfully applied to many classification problems. However, revealing the success rates of KNN and DNN algorithms on the same data set will help researchers working in this field to choose the most suitable model for classification problems.

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The main difference between the KNN and DNN models is that the KNN algorithm does not have a training stage unlike other supervised algorithms. In this study, classification achievements of DNN and KNN models were tested based on this difference. For this purpose, models were created using KNN and DNN classification methods on the "Mobile Price Forecast" dataset. By comparing the estimation performance of the obtained models, it was examined which algorithm gave more successful results in the dataset used. The classification performances of the models were determined using F-1 score, precision, recall and accuracy measurements. In addition, at the end of the study, both models were given a test data that was not labeled with price data, and the classification estimates made by the models were compared.

The following sections of the study are organized as follows; Technical background about KNN and DNN architecture, evaluation measures and dataset are presented in Section 2. While the developed model are explained in Section 3, the test results were evaluated in Section 4.

2. Material and Method

2.1. Dataset

The data set used in the study is the "Mobile Price Classification" training and test dataset, which includes the features of mobile phones and gives the prices of the phones classified according to these features [15]. The training data set consists of 21 columns and 2000 rows. The first 20 columns show the features of the phones such as RAM, 4G, Bluetooth, Battery power, Dual Sim vb., and the 21st column shows the price class of that phone. On the other hand, the second file designated as test data contains 20 columns and 1000 rows of data. In the test dataset, there are the features of the phones in 20 columns, and they are not in what price class.

In Figure 1, distribution graphs and values of battery power, Bluetooth, clock speed, dual sim and front camera megapixel features are given in a part of the training dataset. According to Figure 1, the battery power values of mobile phones are between 501-1998. Likewise, whether a device has Bluetooth capability or not in the data set is labeled with 0-1 values. Also, according to Figure 1, it is seen that the front camera megapixels of mobile phones are labeled between 0-19, and the clutter in the data set is at the value indicated by label 0.

# battery_power	# blue	# clock_speed	# dual_sim	# fc
Total energy a battery can store in one time measured in mAh	Has bluetooth or not	speed at which microprocessor executes instructions	Has dual sim support or not	Front Camera mega pixels
501 – 1998	0 – 1	0.5 – 3	0 – 1	0 – 19
842	0	2.2	0	1
1021	1	0.5	1	0
563	1	0.5	1	2
615	1	2.5	0	0
1821	1	1.2	0	13
1859	0	0.5	1	3

Figure 1. *Example part of Training Dataset*

2.2. K-Nearest Neighbors

K-NN is a classification method based on finding the closest neighbors of the unclassified sample and making predictions according to the classes with high similarity [16]. It is called the lazy learning method or case-based learning method because scanning the data set one by one to find the nearest neighbors reduces the performance of the algorithm [17]. Due to this disadvantage, the k-NN algorithm has a slow running time, especially in large volumes of data [18].

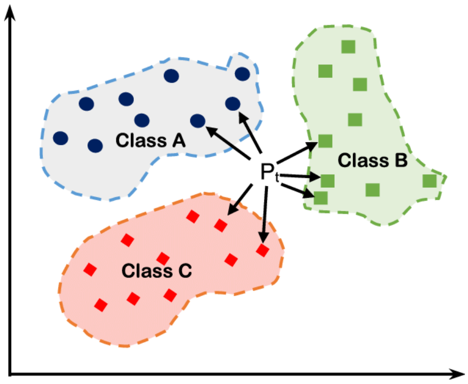

Figure 2. *Visualization of the closest neighbors* [19]

KNN assigns the unclassified sample in a class according to its distance from the previously classified data points [20]. In the Figure 2, the unknown data point P is included in a class according to the minimum distance from the selected k adjacent data points [19]. With this feature, it is among the supervised learning algorithms. Measurement methods used in determining the similarity between data points: Euclidean Distance Eq. (1), Manhattan Distance (2), Chi Square (3), cosine similarity [21].

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{1}$$

$$m(x, y) = \sum_{i=1}^{n} |x_i - y_i| \tag{2}$$

Euclidean Distance and Manhattan Distance are methods also known as Minkowski Distance Methods and where; *xi* and *yi* indicates the points in Cartesian coordinates, whereas *n* indicates the Euclidean space.

$$x^2 = \sum \frac{(O-E)^2}{E} \tag{3}$$

Where; *O* indicates the observed value for each cell, and *E* indicates the expected value. In Chi Square measurement. It was observed that the accuracy rate decreased in data sets with a lot of outlier data because the entire data set contributed to the classification [22].

$$cos\ Q = \frac{x.y}{\|x\|.\|y\|} \tag{4}$$

Where; *x.y* indicates the product of *x* and *y* vectors, ||*x*|| or ||*y*|| indicate length of *x* and *y* vectors.

2.3. Deep Neural Networks

Artificial neural networks are an engineering approach that simulates the parallel processing of millions of interconnected neurons in human brain [23] [24]. Artificial neural networks detect relationships and patterns in dataset and acquire knowledge by experiencing from samplers of previous occasions like humans do, not from conventional programming techniques [25].

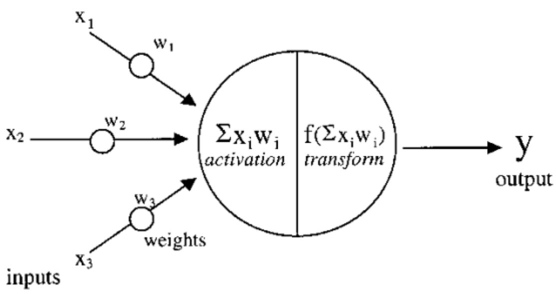

Figure 3. *The Structure of an Artificial Neural* [25]

The inputs, which are the signals reaching the neuron, are summed by multiplying by the connection weights and passed through the objective function to generate an output, as shown in Figure 3 [26]. The structures in which learning takes place by applying the transfer function to the sum of the weighted input values are called artificial neural network [27]. In the most commonly used artificial neural networks; input layers are linked to hidden layers, and hidden layers are linked to the output layer [28]. Wilamowski et al. reported that single hidden layer is insufficient to solving non-linear problems [29]. Also, as seen in the Figure 4, neural networks that have more than one hidden layer besides the input and output layers are called deep neural networks [30].

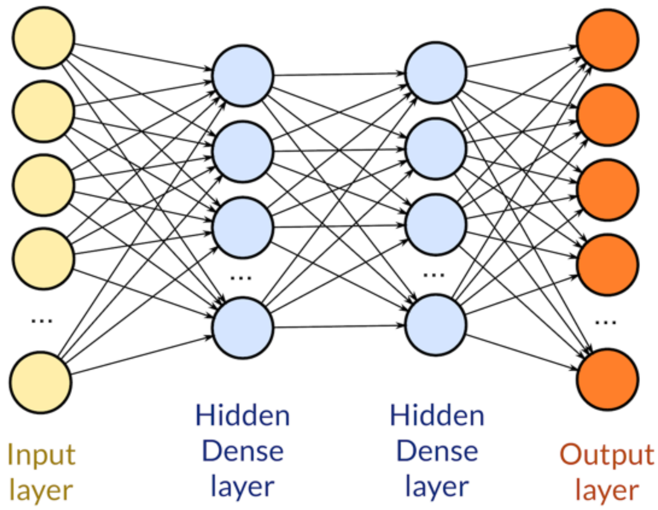

Figure 4. *Deep Neural Network Architecture [30]*

In living beings, the visual process takes place gradually, such as distinguishing the light coming to the eye firstly from the edge, then the size and then the color [31]. In deep neural networks inspired by this biological process, more complex features are learned in each progressive layer, along hidden layers [32] [33]. With the feed forward method, higher-level features are learned by weighing and transmitting information along the connections. The model is trained by updating the weights that were initially selected as very small values. Loss and cost functions are calculated from the predicted value, i.e. the output values, obtained by forward propagation. In the ongoing process called backpropagation, the weights are updated to minimize the cost function which is an initially big value [34]. Learning and predicting occurs by solving classification or regression problems by performing forward and backward propagations sequentially.

2.4. Evaluation Metrics

The Accuracy, precision, recall, F1-score and supports methods used in the evaluation of the study results are explained in this section. Where; TP indicates true positive estimations, TN indicates true negative estimations, FP indicates false positive estimations and FN indicates false negative estimations.

Accuracy: Considering all samples, the ratio of correct predictions to the total number is accuracy. It is given in Eq (5).

$$\frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Precision: It shows how many of the positively predicted values were actually positive. It is given in Eq(6).

$$\frac{TP}{TP+FP} \tag{6}$$

Recall: It shows how many samples that should be predicted positively were predicted positively. It is given in Eq (7).

$$\frac{TP}{TP+TN} \tag{7}$$

F1 Score (F- Measure): F Measure is taken as the harmonic mean of recall and precision to take into account every situation that may be encountered. It is given in Eq (8).

$$\frac{2\ x\ Precision\ x\ Recall}{Precision+Recall} \tag{8}$$

Support: Support value shows how frequently samples are passed in the data. It is given in Eq (9).

$$\frac{Number\ of\ considered\ items}{Number\ of\ total\ samples} \tag{9}$$

3. Prediction of Mobile Phone Prices

In the study, KNN and DNN models were used to estimate the price range of mobile phones. Sklearn library was used in Python to determine the price class of the test data according to the KNN model, and Keras library working on the Tensor Flow platform for the DNN model was used.

Figure 5 shows the stages carried out in the study for the classification of mobile phone prices. First of all, in the preprocessing stage, the training data set is divided into 80% training and 20% validation data. In addition, at this stage, the data was scaled to be in the same range with the Feature Scaling method. During the learning phase, training of the DNN models was carried out by using the training data. On the other hand, KNN is a lazy learning algorithm and it has no learning phase. Later, the validation of the finally models was tested by using the validation data. Finally, the estimation of mobile phone price ranges was made by giving unlabeled test data to both models.

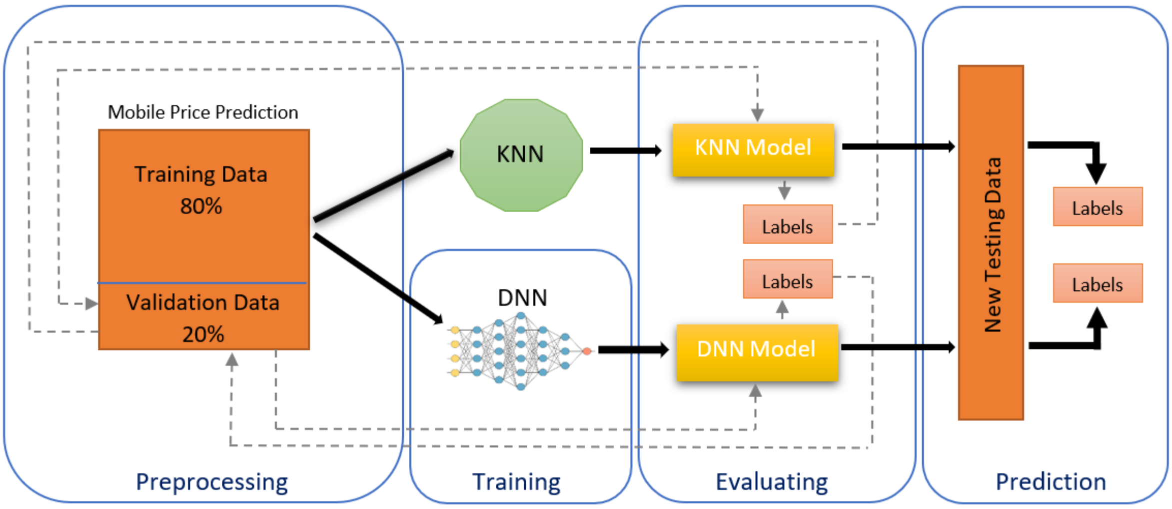

Figure 5. *Mobile phone price estimation stages with KNN and DNN methods*

3.1. KNN Model

The effective and important parameters in the performance of the K-NN algorithm are the number of neighbours (k), the distance criterion and the weighting method. For this reason, the operations performed according to the KNN algorithm for classifying problem of the mobile phones prices can be listed as follows.

(i) The k parameter determines how many nearest neighbours will be used to classify the new value. In the model, the k value is selected as 10.

(ii) Distance values are calculated. The Euclidean distance method was used in the study.

(iii) Uniform is selected as the weighting parameter. This means that each of the k neighbours has equal voting rights, regardless of their distance from the target point.

The classification chart given in Figure 6 was obtained when the KNN model was run according to the parameters determined in the study. According to the chart, it can be seen that mobile phone prices are successfully classified in 4 groups.

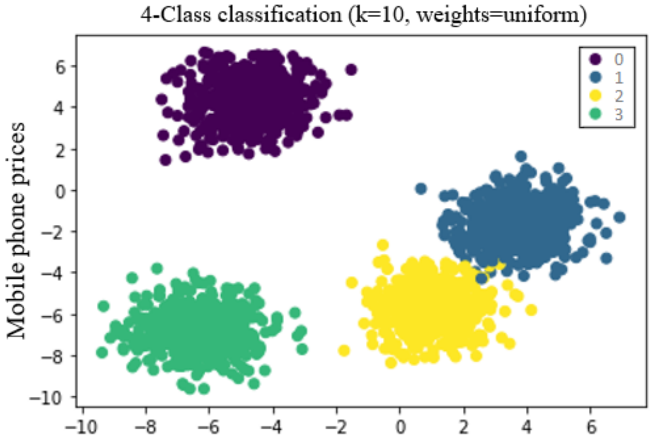

Figure 6. *KNN Classification Graphic*

The Confusion matrix obtained as a result of the classification process with the KNN model is given in Figure 7. As an example, according to Figure 7, 106 of the class 2 mobile phones were correctly identified, and a total of 14 (11 data as class 1, 3 data as class 3) were incorrectly identified. In addition, the most successful estimate was made for the price range determined by class 0. According to the forecast results, 92 data were correctly classified, while 2 data were incorrectly classified and labelled with a value of class 1.

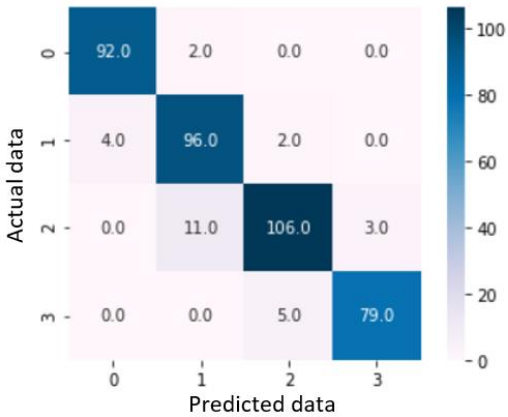

Figure 7. *Confusion Matrix of the KNN Model*

According to the values obtained from the Confusion Matrix given in Figure 7, The evaluation criteria and values showing the classification performance of the KNN algorithm are given in Figure 8. The f1-score score was considered as a priority to decide which model had the best classification performance. According to F1-score values, validation data was estimated with 93% accuracy in the model created by using the KNN algorithm. On the other hand, the fact that the precision and recall values are close to 1 in a model indicates that the performance of the model increases. According to the results obtained, the precision/recall value for each class is quite close to 1. Moreover, weighted avg. supports this situation with a value of 0.93. However, the precision value was higher than the recall value in 2 and 3 labeling. This means that the estimate of other classes is not mixed with this class, but the actual number of estimates that must be for this class is low.

	precision	recall	f1-score	support
0	0.96	0.98	0.97	94
1	0.88	0.94	0.91	102
2	0.94	0.88	0.91	120
3	0.96	0.94	0.95	84
accuracy			0.93	400
macro avg	0.94	0.94	0.94	400
weighted avg	0.93	0.93	0.93	400

Figure 8. *Classification Report of the KNN Model*

3.2. DNN Model

Important parameters that are effective in the performance of DNN algorithm are activation function, optimization algorithm, loss function and epoch. At the application stage of the study, the DNN model was trained for different possible values of these parameters and values with the best classification performance were given in the study.

(i) Activation functions to be used in the layers of the neural network are determined by taking into account the desired output states when creating a DNN model with Keras. In the study, ReLu (Rectified Linear Unit) activation function was used in the input and hidden layers of the model. In addition, the Softmax function is preferred because a categorical classification is performed at the output layer.

(ii) The main component of DSA training is the optimization algorithm. The optimization algorithm defines how a model's parameters are updated. In the study, the Adam (Adaptive moment) algorithm was selected as an optimization algorithm with a learning rate of 0.001.

(iii) The loss function determines the performance of a model and its value is asked to close to 0. Categorical crossentropy was used as a loss function in the study.

(iv) In the study, the model that gave the best classification results was reached in the values of 50 epoch numbers and 20 batch size.

In the DNN model prepared for the classification of mobile phone prices, 20 attributes contained in the dataset refer to the inputs of the model. In the model, the hidden layers are designed to be 16 and 8-dimensional, respectively, and the output layer is designed to be 4 outputs for 4 price classes. The Confusion matrix obtained as a result of the classification process with the DNN model is given in Figure 9. As an example, according to figure 9, 109 of the price Class 2 mobile phones were correctly identified, and a total of 11 (5 data as class 1, 6 data as class 3) were incorrectly identified. In addition, the most successful estimate was made for the price range determined by class 3. According to the forecast results, 82 data were correctly classified, while only 2 data were incorrectly classified and labelled with a value of class 2.

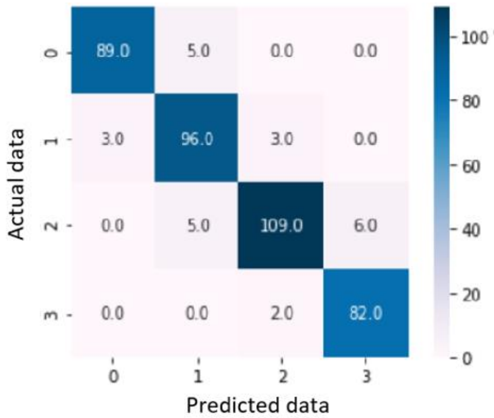

Figure 9. *Confusion Matrix of the DNN Model*

According to these values obtained from the Confusion Matrix given in Figure 9, the criteria and values showing the classification performance of the DNN algorithm are given in Figure 9. According to F1-score values, validation data was estimated with 94% accuracy in the model created with the DNN algorithm. Also, according to the results obtained, the precision/recall value for each class is quite close to 1. Moreover, weighted avg. supports this situation with a value of 0.94. However, the precision value was higher than the recall value in 0 and 2 labeling. This means that the estimate of other classes is not mixed with these classes, but the actual number of estimates that must be for these classes is low.

	precision	recall	f1-score	support
0	0.97	0.95	0.96	94
1	0.91	0.94	0.92	102
2	0.96	0.91	0.93	120
3	0.93	0.98	0.95	84
accuracy			0.94	400
macro avg	0.94	0.94	0.94	400
weighted avg	0.94	0.94	0.94	400

Figure 10. *Classification Report of the DNN Model*

4. Results and Discussions

According to validation data, the achievements of the KNN and DNN models in classifying mobile phone prices were realized with 93% and 94% respectively. Confusion matrix values of models compared to class 0, the KNN model estimated the price class with the best accuracy, the class 1 with equal accuracy in both models, and the class 3 and class 4 with the DNN model predicted more accuracy.

At the latest stage of the study, both models, whose validity was proven, were given mobile phone data that was not labelled with a price class, and tested which price class to estimate for mobile phones. Test data with 1000 different mobile phone features were used here. According to the estimated values of the KNN and DNN models for mobile phones whose price is not clear; the percentage scatter chart of the same and different values is given in Figure 11. According to figure 11, they found the same results for 905 out of 1000 data in both algorithms, while they determined different price classes for 95 mobile phone data. In this case, the models showed a 9.5% difference in determining the price class.

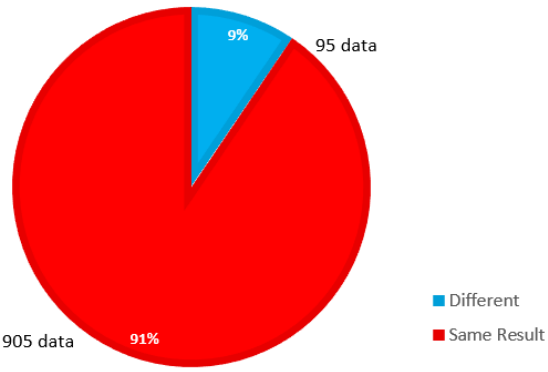

Figure 11. *Comparison of Classification Similarities of DNN and KNN Model*

A graph of the values obtained by the DNN and KNN models in their estimates of the test data is given in Figure 12 for the first 100 data. Looking at the graph, as an example, according to the data in the 20th data row, the KNN algorithm determined the price class of the mobile phone as 2, while the DNN algorithm determined it as 1. Likewise, for the first 100 data, this difference was reflected in the row of the 31, 35, 59, 67, 79, 96 and 100 data.

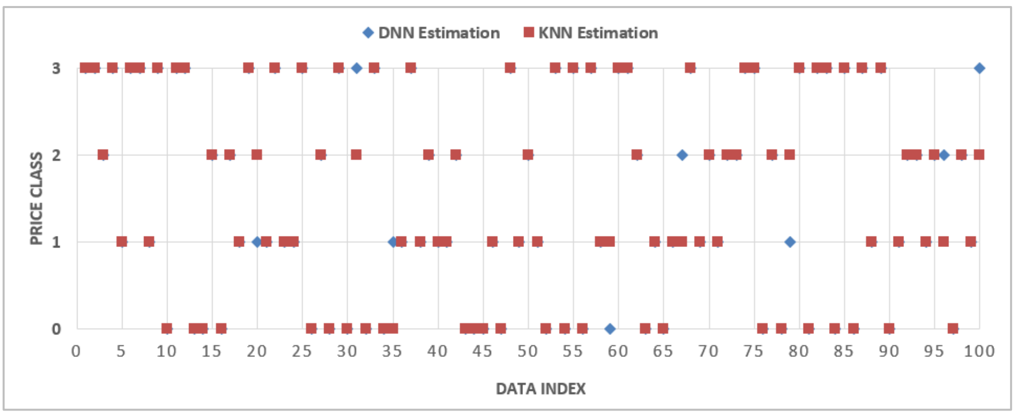

Figure 12. *Comparison of Classification Results of the DNN and KNN Model for first 100 Data*

Looking at the regression results between the classification results made by the KNN and DNN models, it was found that there was a positive linear relationship between the results. For classification data, the linear curve equation was found to be Y = 0.0259 + 0.959 X and R2 value was found to be 0.93. This reveals that the regression fit for both models is good.

5. Conclusions

In the study, the classification achievements of the KNN and DNN models for the mobile phone price classification problem were examined on a data set with the main features that stand out in determining the prices of mobile phones. For this purpose, the data set is primarily divided into training, verification and test data. According to the results obtained from the validation data, KNN was able to classify the data with 93% and DNN 94% accuracy. The study also examined the classification results of both models on a test data with unlabelled data. A 9.5% difference was revealed when comparing different classification values for both algorithms.

According to the results of the study, both models appeared to have high performance in terms of classification skills, but the DNN model, a supervised learning method, showed higher performance. This high performance showed that DNN classifiers are a strong model, taking into account the results given in the literature in general.

Declaration of interest

The authors declare that there is no conflict of interest.

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