Journal of Harbin Engineering University
ISSN: 1006-7043
Vol 45 No. 5
May 2024

The Prediction of 60,000 Fashion Items by the Sequential Model in Deep Learning

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Abstract: The ultimate goal of this paper is to make the sequential model predict what 60,000 pictures about fashion items are in deep learning. A point to note is that when epoch was 24, the accuracy rate of train data was highest, while when epoch was 23, the accuracy rate of validation data was highest. It is worthwhile pointing out that the accuracy of the sequential model is higher than the val_accuracy of the sequential model. This in turn indicates that the sequential model worked well for train data rather than validation data. A further point to note is that the sequential model correctly predicted that 677 fashion items were T-shirts. However, it wrongly predicted that 218 shirts were T-shirts. Quite interestingly, it wrongly predicted that 66 dresses were T-shirts. It is worth noting that there were slight fluctuations in the accuracy rate of the sequential model, but there was a gradual increase in the accuracy of the sequential model. It must be noted that the figure reached a peak when learning took place 25 times (91.20%). A major point of this paper is that the accuracy of the sequential model is slightly higher than the val_accuracy of the sequential model. This in turn suggests that the sequential model worked for train data rather than validation data. It is interesting to observe that the sequential model correctly predicted that 677 fashion items were T-shirts. However, it wrongly predicted that 66 dresses were T-shirts. Also, it wrongly judged 218 shirts as T-shirts. Finally, it must be stressed that the accuracy rate of the sequential model in test data was 83%.

Keywords: AI, Deep Learning, hidden layer, sequential model, accuracy, val_accuracy, loss

1. Introduction

The main purpose of this paper is to make the sequential model predict what 60,000 pictures about fashion items are in deep learning. We obtained these pictures from the datasets of keras. First, we classified 50,000 pictures into train data, whereas we classified 10,000 pictures into test data. Also, we classified 25% of train data (50,000 pictures) into validation data. These 60,000 pictures include the 10 fashion items T-shirt, trouser, pullover, dress, coat, sandal, shirt, sneaker, bag, and ankle boot. First, we trained the sequential model to predict what each fashion item is. In order to improve the accuracy of the sequential model, we used one hidden layer and its node was 128. As activation, we used relu and softmax. It is worth noting that as optimizer, we used adam. It is worthwhile pointing out that when learning took place 25 times, there was a steady increase in the accuracy rate of the sequential model. The figure reached a peak when learning happened 24 times (about 85%). It must be stressed, on the other hand, that when learning took place 25 times, there was a gradual rise in the val_accuracy rate of the sequential model. The figure increased to 84% when learning took place 23 times. That is to say, the figure reached a peak (about 84%) when learning happened 23 times. Second, we attempted to use 4 hidden layers in order to further improve the accuracy of the sequential model. Their nodes were 256, 128, 64, and 32, respectively. As activation, we used relu and softmax, whereas as optimizer, we used adam. It is important to note that when learning took place 25 times, there was

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ISSN: 1006-7043

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a gradual increase in the accuracy rate of the sequential model. The figure reached a peak (about 91%) when learning took place 25 times. It must be pointed out, on the other hand, that there was a steady increase in the val_accuracy of the sequential model. More specifically, the figure increased to 88.71%. In other words, the figure reached a peak (88,71%) when learning took place 24 times.

2. Results

2.1. One Hidden Layer

The goal of this section is to make the sequential model predict what each picture is. We used one hidden layer and used relu and softmax as activation and adam as optimizer. Note that when it comes to one hidden layer, its node is 128. In this section, we aim to inquire into the accuracy rate of the sequential model by using epoch 25. Also, we aim at providing the confusion matrix and classification report.

In what follows, we aim to investigate the accuracy rate of the sequential model by using epoch 25. The following pictures are the relevant samples. That is to say, 20 pictures as only samples were provided, as indicated in Figure 1:

Figure 1 Relevant Samples

Now attention is paid to the accuracy rate, loss, val_loss, and val_accuracy of the sequential model:

Table 1 Epochs

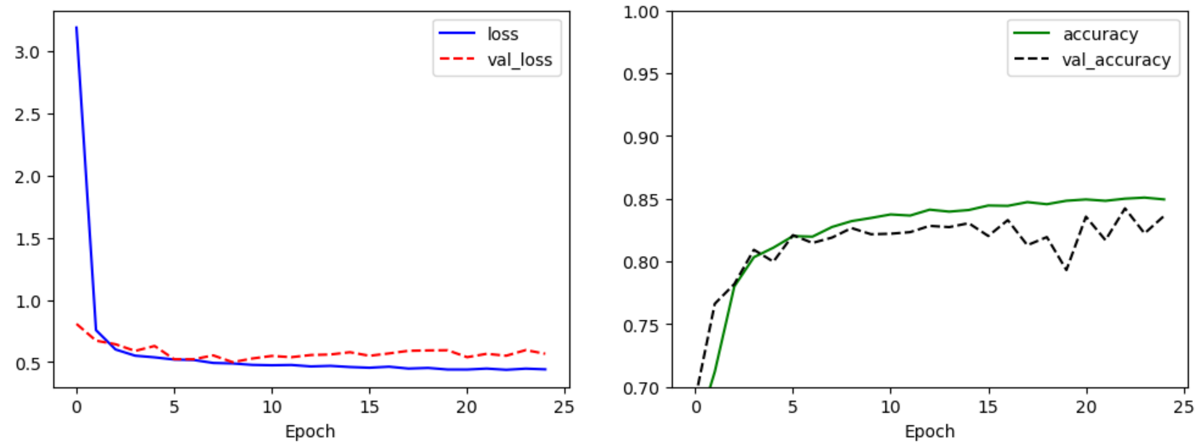
Epoch	Loss	Accuracy	Val_loss	Val_accuracy
Epoch 1	3.1896	0.6607	0.8078	0.6906
Epoch 2	0.7572	0.7121	0.6729	0.7663
Epoch 3	0.6020	0.7801	0.6440	0.7820
Epoch 4	0.5522	0.8033	0.5902	0.8093
Epoch 5	0.5386	0.8110	0.6301	0.7998
Epoch 6	0.5211	0.8202	0.5238	0.8209
Epoch 7	0.5177	0.8197	0.5234	0.8147
Epoch 8	0.4936	0.8274	0.5544	0.8190
Epoch 9	0.4897	0.8321	0.4997	0.8266
Epoch 10	0.4781	0.8346	0.5294	0.8217

Epoch 11	0.4750	0.8374	0.5500	0.8221
Epoch 12	0.4774	0.8366	0.5399	0.8233
Epoch 13	0.4658	0.8412	0.5575	0.8283
Epoch 14	0.4704	0.8397	0.5615	0.8273
Epoch 15	0.4609	0.8410	0.5801	0.8305
Epoch 16	0.4551	0.8446	0.5512	0.8203
Epoch 17	0.4636	0.8443	0.5703	0.8329
Epoch 18	0.4484	0.8473	0.5912	0.8129
Epoch 19	0.4536	0.8456	0.5945	0.8194
Epoch 20	0.4410	0.8484	0.5959	0.7931
Epoch 21	0.4408	0.8494	0.5399	0.8357
Epoch 22	0.4484	0.8483	0.5672	0.8169
Epoch 23	0.4387	0.8500	0.5517	0.8423
Epoch 24	0.4480	0.8509	0.5971	0.8223
Epoch 25	0.4424	0.8494	0.5674	0.8363

The term loss indicates the difference between the answer and the prediction value in train data. As exemplified in Table 1, when epoch was 1, the loss of the sequential model in train data was the highest (3.1896), which in turn indicates that the accuracy rate of the sequential model was also the lowest. It is worthwhile noting that the loss of the sequential model showed slight fluctuations from epoch 1 to epoch 25. Most importantly, when epoch was 23, the loss of the sequential model was the lowest, which in turn indicates that this model worked best when epoch was 23. It is worth pointing out that there was a steady decline in the loss of the sequential model from epoch 1 to epoch 11. After this, there were slight fluctuations in the loss of the sequential model. It is interesting to observe, on the other hand, that the accuracy of the sequential model was the lowest when epoch was 1. Simply put, the accuracy rate of the sequential model was 66.07% (the lowest). It is important to note that when epoch was 24, the accuracy rate of the sequential model was the highest (85.09%). Put differently, the accuracy of the sequential model reached a peak when epoch was 24. It is worth mentioning that there was a gradual rise in the accuracy rate of the sequential model from epoch 1 to epoch 6. After this, there were slight fluctuations in the accuracy rate of the sequential model. The term val_loss indicates the difference between the answer and the prediction value in validation data. Quite interestingly, there was a steady fall in the val_loss of the sequential model from epoch 1 to epoch 4. After this, there were slight fluctuations in the val_loss of the sequential model. Most importantly, the val_loss of the sequential model was the highest when epoch was 1, whereas that of the sequential model was the lowest when epoch was 9. The term val_accuracy indicates that our model in validation data judged true as true, while it judged false as false. It is significant to note that when epoch was 1, the val_accuracy rate of the sequential model was the lowest. It is worth observing that that of the sequential model was the highest when epoch was 23. It is interesting to observe that there was a gradual increase in the val_accuracy of the sequential model from epoch 1 to epoch 4. After this, its figure showed slight fluctuations. We thus conclude that when epoch was 24, the accuracy rate of train data was highest, while when epoch was 23, the accuracy rate of validation data was highest.

Now attention is paid to the loss and val_loss of the sequential model and the accuracy and val_accuracy of the sequential model. The following graphs show the tendency of the loss and accuracy in train data and that of the val_loss and val_accuracy in validation data:

Figure 2 Loss and Val_loss and Accuracy and Val_accuracy



The blue line indicates the loss of the sequential model, as indicated in Figure 2, while the red-dotted line indicates the val_loss of the sequential model. As exemplified in Figure 2, the val_loss of the sequential model is higher than the loss of the sequential model. This in turn suggests that the sequential model worked well for train data rather than validation data. Note that we used 25% of train data as validation data. On the other hand, the green line indicates the accuracy of the sequential model, whereas the brown-dotted line indicates the val_accuracy of the sequential model. As illustrated in Figure 2, the accuracy of the sequential model is higher than the val_accuracy of the sequential model, which in turn indicates that the sequential model worked well for train data rather than validation data.

It is worth pointing out that the loss of the sequential model in test data was 0.5595, while the accuracy rate of the sequential model was 83.07%. This in turn indicates that the loss and accuracy of the sequential model in test data are similar to those of the sequential model in train data.

Now attention is paid to the confusion matrix in train data:

Table 2 Confusion Matrix in train data

677	4	6	66	5	2	218	0	22	0
2	950	6	30	3	1	6	0	2	0
5	1	642	8	208	0	130	0	6	0
8	10	23	824	51	1	72	0	11	0
0	1	65	24	795	0	105	0	10	0
0	0	0	0	0	946	6	28	1	20
79	0	77	38	122	0	635	0	49	0
0	0	0	0	0	27	1	938	1	33
1	1	0	3	2	2	23	5	963	0
0	0	0	0	0	27	0	34	1	938

Quite interestingly, the sequential model correctly predicted that 677 fashion items were T-shirts. Note, however, that it wrongly predicted that 218 shirts were T-shirts. Quite interestingly, it wrongly predicted that 66 dresses were T-shirts. It is important to note that our model correctly predicted that 950 fashion items were trousers. More interestingly, the sequential model correctly predicted that 824 fashion items were dresses. Notice, however, that our model wrongly predicted that 72 shirts were dresses. On the other hand, our model correctly judged 945 fashion items as sandals. However, it wrongly judged 28 fashion items as sneakers. On the other hand, it correctly judged 938 ankle boots as ankle boots. However, it wrongly predicted that 34 ankle boots were sneakers. It is worth pointing out that our model correctly predicted that 963 bags were bags (the highest), whereas it correctly predicted that 635 shirts were shirts (the lowest).

Now let us turn our attention to the classification report:

Table 3 Classification Report

	Precision	Recall	F1-score	Support
0	0.88	0.68	0.76	1000
1	0.98	0.95	0.97	1000
2	0.78	0.64	0.71	1000
3	0.83	0.82	0.83	1000
4	0.67	0.80	0.73	1000
5	0.94	0.94	0.94	1000
6	0.53	0.64	0.58	1000
7	0.93	0.94	0.94	1000
8	0.90	0.96	0.93	1000
9	0.95	0.94	0.94	1000
Accuracy			0.83	10000
Macro avg	0.84	0.83	0.83	10000
Weighted avg	0.84	0.83	0.83	10000

As exemplified in Table 3, the accuracy rate of the sequential model was 83% of 10,000 test data. Our model judged 88% of T-shirts as T-shirts, whereas the proportion of T-shirts in what our model judged as T-shirts was 68%. As indicated in Table 3, our model judged 98% of trousers as trousers, whereas the proportion of trousers in what our model judged as trousers was 95%. On the other hand, our model correctly predicted that 94% of sandals were sandals, whereas the proportion of sandals in what the sequential model judged as sandals was 94%. Finally, our model correctly predicted that 95% of ankle boots were ankle boots. On the other hand, the proportion of ankle boots in what the sequential model judged as ankle boots were 94%. Note that we used 10,000 test data, as shown in Table 3.

2.2. Four Hidden Layers

In the following, we make the sequential model predict what 60,000 pictures are by using four hidden layers. We used relu and softmax as activation and adam as optimizer. The nodes of 4 hidden layers were 256, 128, 64, and 32, respectively. To begin with, we trained the sequential model to predict what each picture is by using epoch 25. Take a look at the following table:

Table 4 Epochs

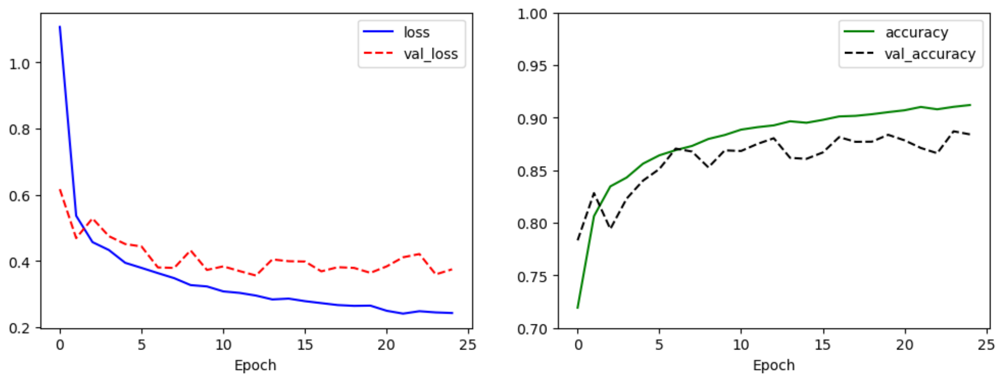
Epoch	Loss	Accuracy	Val_loss	Val_accuracy
Epoch 1	1.1074	0.7193	0.6173	0.7833
Epoch 2	0.5369	0.8064	0.4695	0.8283
Epoch 3	0.4574	0.8346	0.5290	0.7941
Epoch 4	0.4336	0.8431	0.4754	0.8231
Epoch 5	0.3949	0.8563	0.4516	0.8401
Epoch 6	0.3795	0.8642	0.4442	0.8512
Epoch 7	0.3638	0.8692	0.3809	0.8706
Epoch 8	0.3485	0.8731	0.3795	0.8678
Epoch 9	0.3276	0.8798	0.4324	0.8527
Epoch 10	0.3235	0.8835	0.3734	0.8689
Epoch 11	0.3086	0.8886	0.3841	0.8683
Epoch 12	0.3040	0.8910	0.3699	0.8751
Epoch 13	0.2960	0.8927	0.3565	0.8805
Epoch 14	0.2843	0.8966	0.4052	0.8618
Epoch 15	0.2868	0.8952	0.3998	0.8609

Epoch 16	0.2791	0.8979	0.3988	0.8669
Epoch 17	0.2732	0.9012	0.3691	0.8815
Epoch 18	0.2673	0.9018	0.3816	0.8771
Epoch 19	0.2649	0.9033	0.3795	0.8772
Epoch 20	0.2656	0.9053	0.3646	0.8837
Epoch 21	0.2500	0.9071	0.3841	0.8785
Epoch 22	0.2415	0.9102	0.4116	0.8712
Epoch 23	0.2487	0.9080	0.4215	0.8662
Epoch 24	0.2451	0.9103	0.3599	0.8871
Epoch 25	0.2433	0.9120	0.3753	0.8841

It is worthwhile pointing out that as exemplified in Table 4, there was a gradual decline in the loss of the sequential model in train data from epoch 1 to epoch 14. More interestingly, the loss of the sequential model in train data was the highest when epoch took place for the first time. Put differently, when learning took place for the first time, the loss of the sequential model was 1.1074. The figure reached a peak (1.1074). It is important to note that when epoch was 22, the loss of the sequential model was the lowest. It should be pointed out that the figure showed slight fluctuations from epoch 1 and to epoch 25. Note, however, that there were slight fluctuations in the loss of the sequential model, but there was a steady decline in that of the sequential model. It is worth noting, on the other hand, that there was a gradual rise in the accuracy rate of the sequential model from epoch 1 to epoch 14, but after this, there were slight fluctuations. Notice, however, that there were slight fluctuations in the accuracy rate of the sequential model, but there was a gradual increase in the accuracy of the sequential model. It must be noted that the figure reached a peak when learning took place 25 times (91.20%). It must be stressed that the accuracy rate of the sequential model was the lowest (71.93%) when learning happened for the first time. More interestingly, there were slight fluctuations in the val_loss of the sequential model from epoch 1 to epoch 25. Note, however, there was generally a steady drop in the val_loss of the sequential model in validation data. It is appropriate to contend that when learning took place 13 times, the val_loss of the sequential model was the lowest (0.3565). It is worthwhile noting that when learning happened for the first time, the val_loss was the highest (0.6173). Finally, attention is paid to the val_accuracy of the sequential model in validation data. There were slight fluctuations in the val_accuracy of the sequential model, but there was a gradual increase. It must be pointed out that when learning took place 24 times, the figure reached a peak (88.71%). It is worth noticing, on the other hand, that the val_accuracy of the sequential model was the lowest (78.33%) when learning happened for the first time. It seems reasonable to conclude that when epoch was 24, the val_accuracy increased to 88.71% (the highest) in validation data.

Now let us turn our attention to two graphs. The following two graphs show the tendency of the loss and val_loss and the accuracy and val_accuracy of the sequential model:

Figure 3 Loss and Val_loss and Accuracy and Val_accuracy



The blue line indicates the loss of the sequential model, whereas the red-dotted line indicates the val_loss of the sequential model. Quite interestingly, there was a gradual fall in the loss of the sequential model, as illustrated in Figure 3. The figure decreased to about 0.2. On the other hand, there were slight fluctuations in the val_loss of the sequential model. The figure decreased to about 0.3. Most importantly, the val_loss of the sequential model is higher than the loss of the sequential model, which in turn indicates that the sequential model worked well for train data rather than validation data. As shown in Figure 3, the green line indicates the accuracy of the sequential model, whereas the brown-dotted line indicates the val_loss of the sequential model. As indicated in Figure 3, there was a steady increase in the accuracy of the sequential model, but there were slight fluctuations in the val_loss of the sequential model. When it comes to the loss of the sequential model, the figure increased to about 91%, whereas talking about the val_loss of the sequential model, the figure increased to about 88%. Most interestingly, the accuracy of the sequential model is slightly higher than the val_accuracy of the sequential model, which in turn suggests that the sequential model worked for train data rather than validation data.

Quite interestingly, the loss of the sequential model in test data was 0.4253, whereas the accuracy rate of the sequential model was 87.25%. This in turn implies that the loss of the sequential model in test data is slightly higher than the loss of the sequential model in train data. On the other hand, the accuracy rate of the sequential model in train data is slightly higher than that of the sequential model in test data. From all of this, it seems clear that the sequential model worked well for train data rather than test data.

Now let us turn our attention to the confusion matrix:

Table 5 Confusion Matrix

677	4	6	66	5	2	218	0	22	0
2	950	6	30	3	1	6	0	2	0
5	1	642	8	208	0	130	0	6	0
8	10	23	824	51	1	72	0	11	0
0	1	65	24	795	0	105	0	10	0
0	0	0	0	0	945	6	28	1	20
79	0	77	38	122	0	635	0	49	0
0	0	0	0	0	27	1	938	1	33
1	1	0	3	2	2	23	5	963	0
0	0	0	0	0	27	0	34	1	938

As illustrated in Table 3, the sequential model correctly predicted that 677 fashion items were T-shirts. However, it wrongly predicted that 66 dresses were T-shirts. Also, it wrongly judged 218 shirts as T-shirts. As indicated in Table 5, the sequential model correctly predicted that 950 fashion items were trousers. However, it wrongly judged 30 dresses as trousers. Quite interestingly, it correctly predicted that 824 fashion items were dresses. Note, however, that it judged 72 shirts as dresses. More interestingly, it correctly judged 635 fashion items as shirts. However, it wrongly judged 122 coats as shirts. It is interesting to observe that it correctly predicted that 938 fashion items were ankle boots. However, it wrongly judged 34 sneakers as ankle boots. It is significant to note that the accuracy of the sequential model with respect to pullovers were the lowest, whereas that of the sequential model with regard to trousers were the highest.

Finally, attention is paid to the classification report:

Table 6 Classification Report

	Precision	Recall	F1-score	Support
0	0.83	0.72	0.77	1000
1	0.97	0.96	0.97	1000
2	0.72	0.74	0.73	1000
3	0.92	0.77	0.83	1000
4	0.77	0.68	0.72	1000
5	0.95	0.95	0.95	1000
6	0.49	0.71	0.58	1000
7	0.88	0.96	0.92	1000
8	0.97	0.91	0.94	1000
9	0.97	0.89	0.92	1000
Accuracy			0.83	10000
Macro avg	0.85	0.83	0.83	10000
Weighted avg	0.85	0.83	0.83	10000

As exemplified in Table 6, the total number of test data is 10,000. The term support indicates the number of test data. The term precision indicates that our model judged true as true. On the other hand, the term accuracy indicates that our model judged true as true and judged false as false. The term recall indicates the proportion of truth in what our model judged as true. Quite interestingly, the accuracy rate of the sequential model in test data was 83%. As indicated in Table 6, our model correctly predicted that 83% of T-shirts were T-shirts. The proportion of T-shirts in what our model judged as T-shirts was 72%. Additionally, our model judged 97% of trousers as trousers. On the other hand, the proportion of trousers in what our model judged as trousers was 97%. Quite interestingly, our model judged 49% of shirts as shirts, which in turn indicates that the figure was the lowest. More interestingly, our model judged 97% of bags as bags. The proportion of bags in what our model judged as bags was 91%. Exactly the same can be said of ankle boots. Their precision was 97%, which in turn indicates that our model predicted that 97% of ankle boots were ankle boots. Note that the proportion of ankle boots in what the sequential model judged as ankle boots was 89%. It can thus be concluded that the accuracy rate of the sequential model with respect to test data was 83%. For the anlayses of big data, machine learning, and deep learning, see Kang (2014a, 2014b, 2014c, 2014d, 2014e, 2014f, 2024g).

3. Conclusion

To sum up, we have made the sequential model predict what 60,000 pictures about fashion items are in deep learning. In section 2.1, we have maintained that when epoch was 24, the accuracy rate of train data was highest, while when epoch was 23, the accuracy rate of validation data was highest. Also, we have maintained that the accuracy of the sequential model is higher than the val_accuracy of the sequential model. This in turn indicates that the sequential model worked well for train data rather than validation data. We have further argued that the sequential model correctly predicted that 677 fashion items were T-shirts. However, it wrongly predicted that 218 shirts were T-shirts. Quite interestingly, it wrongly predicted that 66 dresses were T-shirts. In section 2.2, we have contended that there were slight fluctuations in the accuracy rate of the sequential model, but there was a gradual increase in the accuracy of the sequential model. It must be noted that the figure reached a peak when learning took place 25 times (91.20%). In section 2.2, we have further argued that the accuracy of the sequential model is slightly higher than the val_accuracy of the sequential model. This in turn suggests that the sequential model worked for train data rather than validation data. Also, we have contended that the sequential model correctly predicted that 677 fashion items were T-shirts. However, it wrongly predicted that 66 dresses were T-shirts. Also, it wrongly judged 218 shirts as T-shirts. Finally, we have argued that the accuracy rate of the sequential model in test data was 83%. As indicated in Table 6, our model correctly predicted that 83% of T-shirts were T-shirts. The proportion of T-shirts in what our model judged as T-shirts was 72%.

References

[1] Kang, N (2024a). A Big Data Analysis of a Hot Political Issue. *Studies in Linguistics* 70, 149-165
[2] Kang, N (2024b). The Ukrine War in BBC News: A Big Data Analysis. *International Journal of Applied Engineering and Technology* 6(1), 1548-1555
[3] Kang, N (2024c). A Study of the Prediction of the Model Logistic Regression in Machine Learning: Focusing on a Survey. *Semiconductor Optoelectonics* 43(1), 86-94
[4] Kang, N (2024d). The Spring of Seoul: A Big Data Analysis. *Semiconductor Optoelectonics* 43(1), 264-272
[5] Kang, N (2024e). A Study of the Prediction of the Three Models Logistic Regression, Gaussian Naive Bayes, and Multi-Layer Perceptron Classifier in Machine Learning. *Semiconductor Optoelectonics* 43(1), 253-263
[6] Kang, N (2024f). An Analysis of the Prediction Power of Four Models in Machine Learning and Deep
[7] Learning: Focusing on the Reviews of the Movie Noryang. *A Jungang Journal of English Language and Literature* 66(1), 101-122
[8] Kang, N(2024g). An Association Analysis of Shopping Items in Machine Learning. Stochastic Modelling and Computational Sciences 4(1), 97-109