Hindawi

Retraction

Retracted: Prediction Model of Rotor Yarn Quality Based on CNN-LSTM

Journal of Sensors

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Z. Hu, "Prediction Model of Rotor Yarn Quality Based on CNN-LSTM," *Journal of Sensors*, vol. 2022, Article ID 3955047, 12 pages, 2022.

Hindawi

Research Article
Prediction Model of Rotor Yarn Quality Based on CNN-LSTM

Zhenlong Hu

Jiyang College, Zhejiang A&F University, Zhuji, 311800 Zhejiang, China

Correspondence should be addressed to Zhenlong Hu; 20208120@zafu.edu.cn

In the whole textile industry chain, yarn production is one of the key links, which has a great impact on the quality of textile and clothing products. For a long time, the textile industry has been hoping for a yarn quality prediction technology, which can accurately predict the final yarn quality indicators according to the known conditions such as raw materials and production processes. CNN-LSTM yarn prediction model is a deep neural network model based on the assumption that the influence of textile processing time series on yarn quality is considered. CNN optimizes the input eigenvalues through one-dimensional convolution and pooling, and LSTM matches the optimized fiber performance indexes and process parameters in time series according to the processing sequence and excavates their laws, thus realizing the goal of predicting yarn quality indexes. The effects of input fiber performance index, process parameters, convolution kernel parameters, pool kernel parameters, LSTM unit number, LSTM layer number, and optimization algorithm on prediction accuracy were studied, and the parameters of CNN-LSTM model were determined. Experiments on the data set of spinning yarn show that the mean square error (MSE) of CNN-LSTM model in predicting yarn strength, Dan Qiang unevenness, evenness unevenness, and total neps is lower than that of linear regression model and BP neural network. At the same time, it is found that the prediction accuracy of CNN-LSTM model is greatly influenced by process parameters and optimization algorithm.

1. Introduction

The practical significance of this project is to solve the practical problems in the production of yarn factories. Yarn factories often encounter problems such as different batches of fiber raw materials and the need to renovate varieties. How to maintain the stability of yarn quality indicators is a problem that the quality managers of yarn production enterprises pay most attention to. In order to solve these problems, the usual practice of spinning enterprises is to feed the yarn for trial spinning, then test the yarn quality index through sampling inspection, and then adjust the process parameters before continuing the test until a better configuration and process are found. This method is not only easy to cause huge waste of raw materials, manpower, and material resources but also has long cycle and low efficiency. At present, spinning mills urgently need modern technology that can accurately predict various spinning quality indexes before spinning.

A yarn quality prediction model is a model that reflects the relationship between yarn quality indicators and fiber performance indicators, spinning process parameters, and finished yarn specifications. The more accurately the prediction model expresses the essential relationships, then the higher the prediction accuracy of the model, which is the common goal pursued by researchers. Through the reading and analysis of Chinese and foreign literature, it can be summarized that yarn quality prediction models at home and abroad have gone through two development stages: the first one is the mathematical and statistical model stage, with regression models as representative; the second one is the shallow machine learning stage, with support vector machines and BP neural networks as representative. From an overall perspective, the development of yarn quality prediction methods is at the same time a process of increasing prediction accuracy. From another point of view, it is the process of expressing the relationship between fiber properties and process indicators and yarn quality indicators more and more precisely. In order to use yarn quality forecasting in real production, the forecasting accuracy needs to be further improved and the relationship between fiber properties, process timing and its parameters, and yarn quality needs to
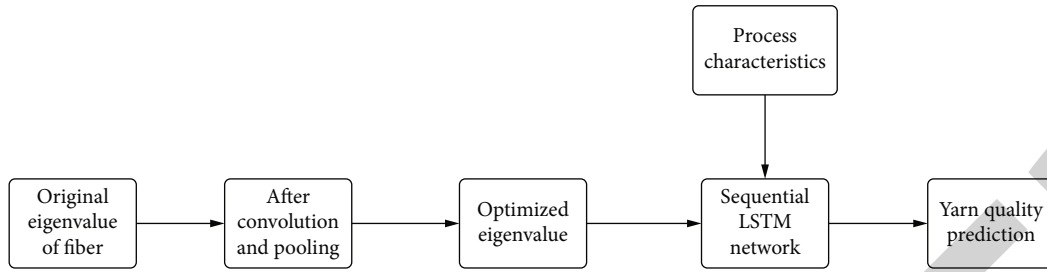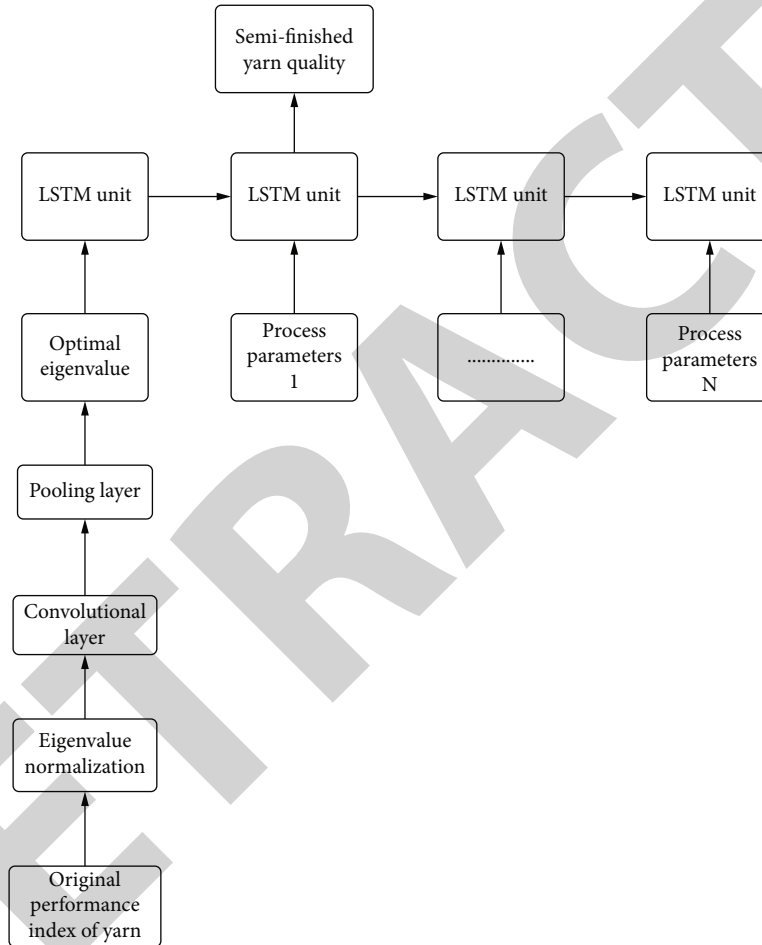
FIGURE 1: Thinking of CNN-LSTM model design.

FIGURE 2: Structure of CNN-LSTM model design.

be more accurately expressed. To achieve these goals, a deeper and more accurate representation is needed through a time-series deep neural network, which can further improve the prediction accuracy. In such a context, this paper proposes to establish a temporal deep neural network CNN-LSTM yarn quality prediction model [1–6].

2. Related Works

Yarn quality prediction methods are mainly divided into mathematical statistics methods and machine learning methods. The specific research is as follows:

CSIRO et al. [7] established team equation in wool spinning field by using linear regression method. Its prediction result is average, and the prediction accuracy is not high, and it is mainly for Australian wool. For wool from other places, the prediction result error is large. On the basis of team equation, CSIRO also developed yarnspec prediction system, which has three models: yarn strength, yarn evenness, and yarn breakage rate. The main problem is that the prediction accuracy is not high.

Chen Dongsheng [8] used the grey system model to analyze the relationship between flax fiber indexes and flax yarn quality. The analysis results showed that flax fiber splitting index had the greatest impact on yarn quality, flax fiber

$$(X_{11} \ X_{12} \ X_{13} \ X_{14} \ X_{21} \ X_{22} \ X_{23} \ X_{24} \ X_{31} \ X_{32} \ X_{33} \ X_{34} \ X_{41} \ X_{42} \ X_{43} \ X_{44})^{\mathrm{T}}$$

Figure 3: CNN-LSTM neural network input vector.

Table 1: Description of symbols in Chinese and English.

Number	Name
X_{11}	Cotton fiber body length
X_{12}	Cotton fiber maturity
X_{13}	Cotton fiber breaking strength
X_{14}	Cotton fiber uniformity
X_{21}	Cotton fiber linter rate
X_{22}	Upper half length of cotton fiber
X_{23}	Specific strength of cotton fiber
X_{24}	Total cotton fiber defects
X_{31}	Impurity content of cotton fiber
X_{32}	Moisture regains of cotton fiber
X_{33}	Yellow degree of cotton fiber +b
X_{34}	Cotton fiber micronaire value
X_{41}	Cotton fiber reflectivity
X_{42}	Rotating speed of cotton opener
X_{43}	Rotating speed of carding roller
X_{44}	Rotating speed of rotor

length had the lowest impact, and the impact of flax fiber strength was between the two. The relationship model between flax yarn quality indexes (yarn breaking elongation and yarn size) and flax fiber performance indexes is established. Using this model to predict, the flax yarn quality prediction index is relatively ideal, the residual error between the measured value and the predicted value of the trial spun yarn size is 0.0629, and the residual error between the measured value and the predicted value of the trial spun yarn breaking length is 0.478.

Song Chuping and Cai Binbin [9] proposed a yarn quality prediction method combining SVM and GA (genetic algorithm, GA). Taking 5 fiber indexes such as fiber length and 4 process parameters as input and yarn strength as output, the relative error is 2.2%. This method can be well applied to the prediction of multivariety, small batch, and personalized yarn production.

Wang Kanfeng et al. [10] used a three-layer shallow artificial neural network to predict the quality of combed wool yarn. The input is 11 indicators such as fiber fineness and fineness unevenness, and the output is quality indicators such as yarn unevenness, coarse and fine knots, and breakage rate. Because the factors of the formation of the decapitation rate are complex, a combined neural network model is designed. The results show that the predicted values of six indicators are ideal, and the correlation coefficient with the measured values exceeds 0.9, indicating that artificial neural network has a wide application prospect in yarn prediction.

Zhang Wei [11] designed a convolutional neural network according to the mobile net model, which can classify

the principal components of cotton, Tencel, polyester, wool, and acrylic fabrics with an accuracy of 96.53%.

To sum up, the method based on data statistics can clearly determine the relationship between the original eigenvalues of input fibers and processes and the final yarn quality, but the prediction accuracy is low. The prediction accuracy of machine learning based methods is much higher than that of data statistical methods, but most of them use traditional neural networks and other methods. Advanced deep learning methods are rarely used and do not pay attention to the impact of textile process timing on yarn quality. This paper is based on the deficiencies of the above research status.

3. Materials and Method

3.1. CNN-LSTM Neural Network Model Design Ideas. The CNN-LSTM neural network model is a model designed to fully consider the effect of yarn processing timing and parameters on yarn quality, as shown in Figure 1.

Figure 1 illustrates that the original fiber feature values are first optimized and dimensional zed by convolution and pooling operations, and then these optimized feature values are fed into the LSTM temporal neural network, and finally the corresponding predicted values of yarn quality indicators are output. For the sake of simplicity, the CNN-LSTM neural network model is abbreviated as CNN-LSTM model in the following.

As shown in Figure 1, the model consists of 6 parts. In the first part, it inputs the original fiber attribute value. In the second part, these attribute values are normalized, convoluted, and pooled. In the third part, it further optimizes the output value of the previous part. In the fourth part, these optimized feature values and process parameters are fed into the LSTM temporal neural network. Finally, the corresponding predicted values of yarn quality indicators are output. The CNN-LSTM neural network model is abbreviated as CNN-LSTM model in the following.

3.2. CNN-LSTM Model Structure. The structure of CNN-LSTM model is shown in Figure 2.

As shown in Figure 2, firstly, various performance indexes of normalized fibers are input and arranged into n-dimensional feature vectors from top to bottom according to the sequence; Then, after one-dimensional convolution and one-dimensional pooling, the optimized eigenvalue is finally input into the first time-series node of LSTM neural network, then the normalized processing parameter 1 is input at the second time-series node, and so on until the process parameter N is input, each node in the middle can output the semi-finished yarn quality index, and the final node can output the finished yarn quality index.

3.3. Parameter Setting of CNN-LSTM Model. Parameter setting of CNN-LSTM model mainly includes input layer
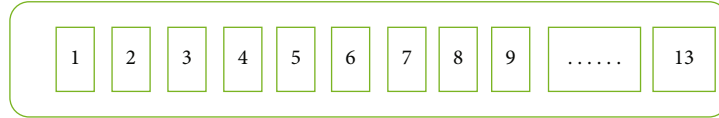
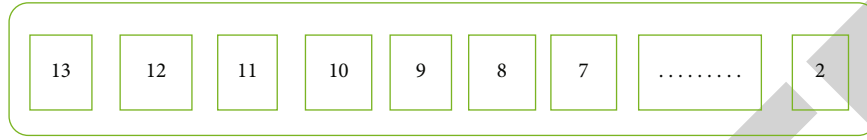FIGURE 4: Structure diagram of convolution module.
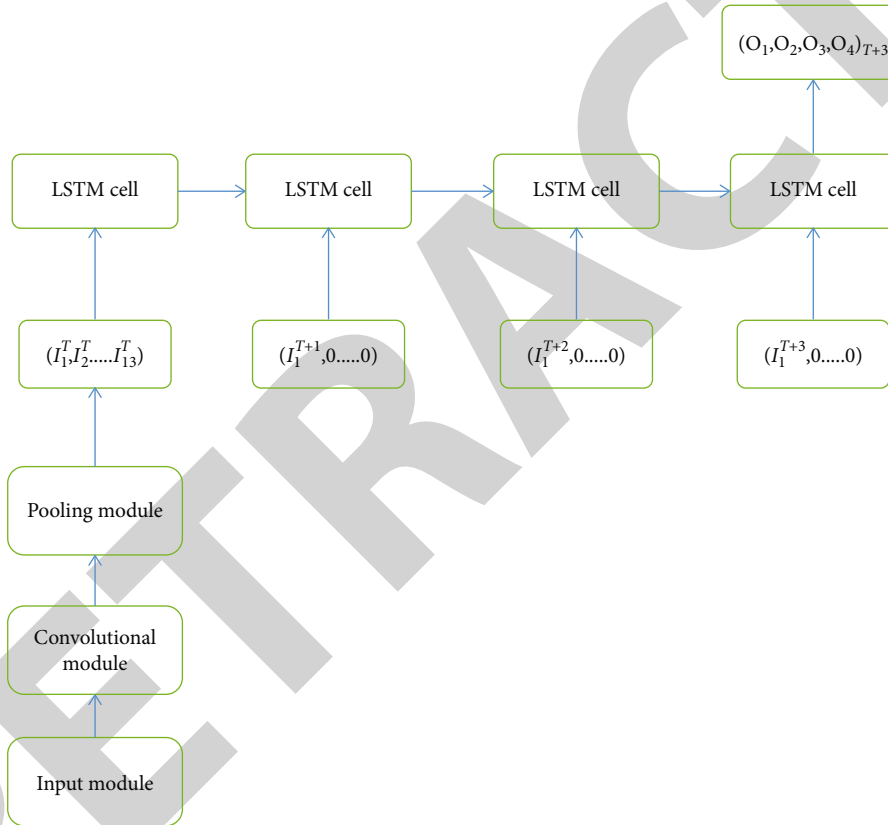

FIGURE 5: Pool layer structure diagram.

FIGURE 6: LSTM network model structure diagram.

structure, convolution layer structure, activation function design, pool layer structure, LSTM layer structure, and output layer structure [12–15]. Because spinning methods, technological processes, and equipment are not static, it is necessary to combine specific conditions in specific operations. In this section, the parameter setting of CNN-LSTM model is illustrated by taking the cotton yarn produced by a spinning factory in Zhejiang as an example.

The specific process flow of a factory in Zhejiang is FA009 reciprocating cotton picker →FA105A uniaxial cotton opener →FA029 multi-bin cotton mixer →FA231 carding machine →FA306 drawing frame →RS30 rotor spinning machine.

3.3.1. Input Layer. Input layer inputs N-dimensional fiber performance index feature vector. Take rotor yarn quality prediction as an example, as shown in Figure 3.

As shown in Figure 3, the input is a column vector. The meanings from X_{11} to X_{44} are shown in Table 1. After normalization, the performance index data of cotton fibers are arranged into longitudinal 13-dimensional vectors in the order shown in Figure 3, which are input into the model.

3.3.2. Convolution Layer. As shown in Figure 4, the convolution layer is 1 layer. Because there are no fixed rules and formulas for the definition of convolution kernel, this paper converts all the combinations from part to whole into

TABLE 2: Main parameters of CNN-LSTM model.

Parameter name	Specific parameters
Number of convolution layers	1 layer
Number of convolution kernels	13
Activate function	ReLU
Number of pooling layers	1 layer
Number of pooled cores	12
LSTM neural network layer number	One
LSTM hidden layer node number	16
Output layer parameters	Four
Loss function	Mean square error function (MSE)
Initial value of learning rate	0.01
Training data	One hundred and eighty
Test data	20
Epoch	100

TABLE 3: Comparison table of predicted values of rotor yarn strength by three algorithms. Unit: cN/tex.

Serial number	Actual value	CNN-LSTM	BP	Regression algorithm
1	16.4	16.4	16.0	17.0
2	16.1	16.1	15.9	16.0
3	15.4	15.5	15.0	16.1
4	14.9	14.9	14.0	15.5
5	14.8	14.7	14.6	15.1
6	14.8	14.9	14.8	15.5
7	15.6	15.4	15.0	15.0
8	15.2	15.2	14.9	14.5
9	14.7	14.8	14.3	14.0
10	14.5	14.6	14.2	15.0
11	14.8	14.7	14.2	15.2
12	14.8	14.7	14.0	14.0
13	15.2	15.2	14.8	14.5
14	14.8	14.7	15.1	15.3
15	14.9	15.0	15.3	15.4
16	15.4	15.2	15.8	16.0
17	15.7	15.8	16.0	16.2
18	15.7	15.7	16.0	16.2
Mean absolute difference		0.080	0.400	0.556
Average relative error		0.008	0.026	0.037
Mean square error (MSE)		0.010	0.203	0.336
Root-mean-square error		0.110	0.451	0.579
R square		0.990	0.870	0.560

TABLE 4: Comparison of predicted values of two models for single intensity unevenness. Unit: %.

Serial number	Actual value	CNN-LSTM	BP	Regression algorithm
1	9.2	9.2	10	10.1
2	13.5	13.5	13	12.5
3	9.5	9.4	10	8
4	10.9	10.8	11.2	10
5	11.3	11.1	11	10.5
6	12.1	12.1	12.4	11.5
7	8.9	8.9	9.1	10
8	9.9	9.8	10.2	11
9	9.2	9.2	9	10
10	13.5	13.4	14	15
11	9.5	9.5	10.5	11
12	10.9	10.8	11.2	11.8
13	11.3	11.2	11.5	118
14	12.1	12.1	12.5	12.9
15	8.9	8.9	9.2	9.5
16	9.9	9.9	10.2	10.6
17	11.4	11.4	11.7	11.9
18	11.5	11.3	11.8	11.9
Mean absolute difference		0.055	0.450	0.566
Average relative error		0.005	0.036	0.047
Mean square error (MSE)		0.009	0.223	0.436
Root-mean-square error		0.098	0.461	0.589
R square		0.990	0.880	0.550

convolution kernels, that is, there are 13 one-dimensional convolution kernels with the length from 1 to 13.

$$M = (W - F + 2P)/S + 1. \qquad (1)$$

As shown in Equation (1), M is the matrix after convolution, W is the input matrix, F is the convolution kernel size, P is the padding size, and S is the step size. In this example, p is 0, and $S = 1$, then a 13-dimensional eigenvector, a 12-dimensional eigenvector, and so on can be obtained after the 13-dimensional input value passes through the convolution layer.
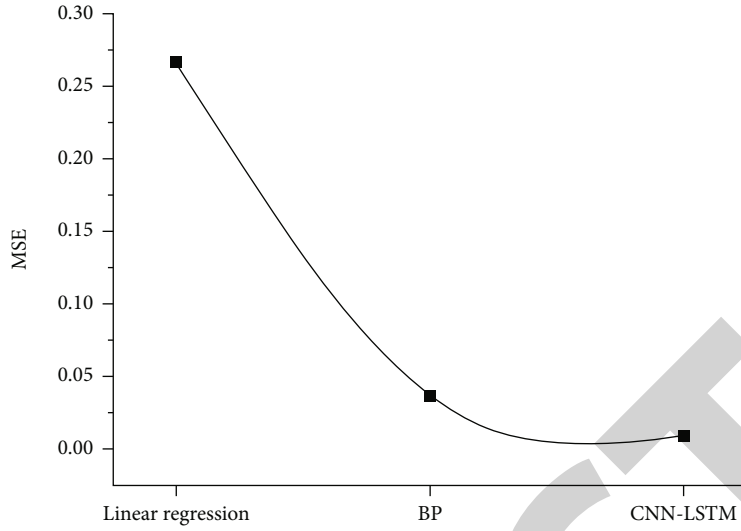
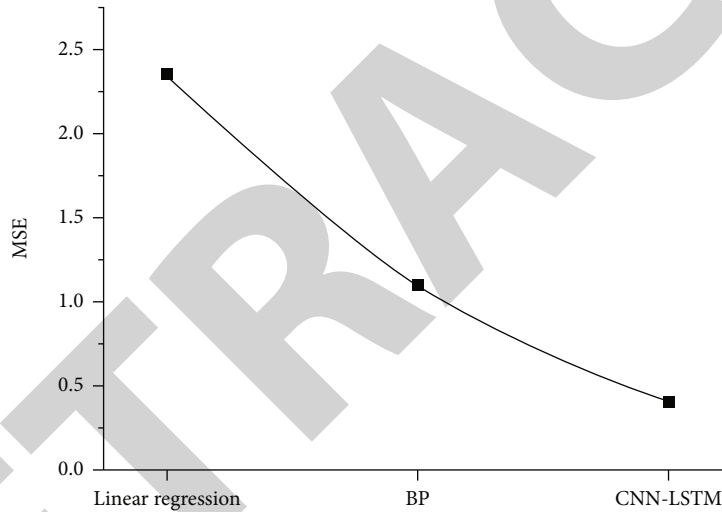FIGURE 7: MSE of predicted value of Tiao Gan unevenness of rotor yarn by three models.

FIGURE 8: MSE of the predicted value of the total number of cotton impurities in rotor yarn by three models.

3.3.3. Activate Function. The main function of activation function is to transform linear expression into nonlinear expression. Due to the long back propagation distance of CNN-LSTM model, in order to prevent the gradient from disappearing, the convolution layer adopts ReLU (Corrected Linear Units, abbreviated as RELU) activation function, and its expression is shown in Formula (2).

$$\text{ReLU}(x) = \max\,(0, x). \tag{2}$$

3.3.4. Pooling Layer Structure. As shown in Figure 5, there is only one pool layer, and the pool cores are, respectively, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, and 2 in length. Max-pooling algorithm is adopted, that is, the largest and most significant eigenvalues are selected from the 12 eigenvectors output by convolution layer, and finally, 12 eigenvalues can be obtained and input to the next layer.

3.3.5. LSTM Neural Network Layer. LSTM neural network is a time-series network, and the process parameters should be input according to the sequence of yarn processing time after normalization.

As shown in Figure 6, $(I_1^T, I_2^T, ..., I_{13}^T)$ represent the input vectors, (O_1, O_2, O_3, O_4) represent the output vectors, and $T, T+1, T+2$, and $T+3$ represent the time series. The output vector from the pooling layer is $(I_1^T, I_2^T, ..., I_{13}^T)$. This vector is then fed into the LSTM neural network at moment T. Because the LSTM neural network is actually a sequence of the same network at different times, the input dimension should be the same each time [16–19]. At the moment of $T+1$, the input has only 1 bit value, so it is necessary to use 0 to make up the 13 bits, i.e., $(I_1^{T+1}, 0, 0, 0, 0, 0, ..., 0)$, where I_1^{T+1} is the speed of the cotton opener (r/min). Similarly, input $(I_1^{T+2}, 0, 0, 0, 0, 0, ..., 0)$ at the moment of I_1^{T+2}, where $(I_1^{T+2}, 0, 0, 0, 0, 0, ..., 0)$ is the speed of carding roller (r/min). Input $(I_1^{T+3}, 0, 0, 0, 0, 0, ..., 0)$ at the
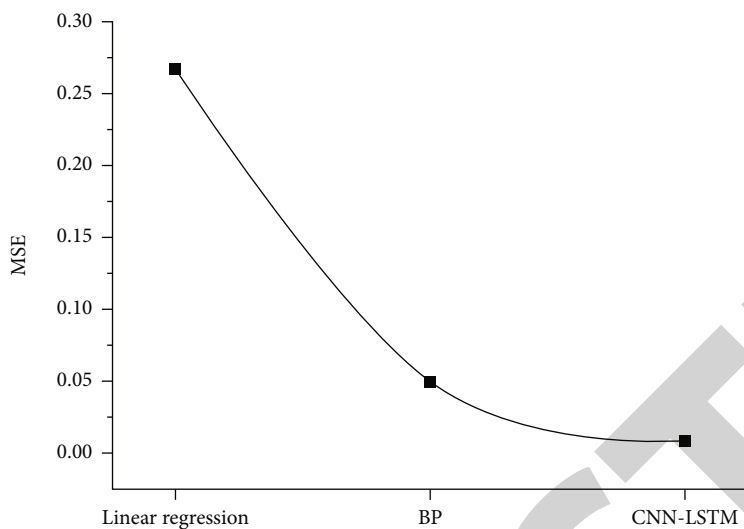
Figure 9: MSE of predicted value of Dan Qiang unevenness of rotor yarn by three models.

Table 5: CNN-LSTM model parameter setting table.

Parameter name	Specific parameters
Number of convolution layers	1 layer
Number of convolution kernels	13
Activate function	ReLU
Number of pooling layers	1 layer
Number of pooled cores	12
LSTM neural network layer number	One
LSTM hidden layer node number	16
Output layer parameters	Four
Loss function	Mean square error function (MSE)
Initial value of learning rate	0.01
Training data	One hundred and eighty
Test data	20
Epoch	100

Table 6: Input feature arrangement scheme.

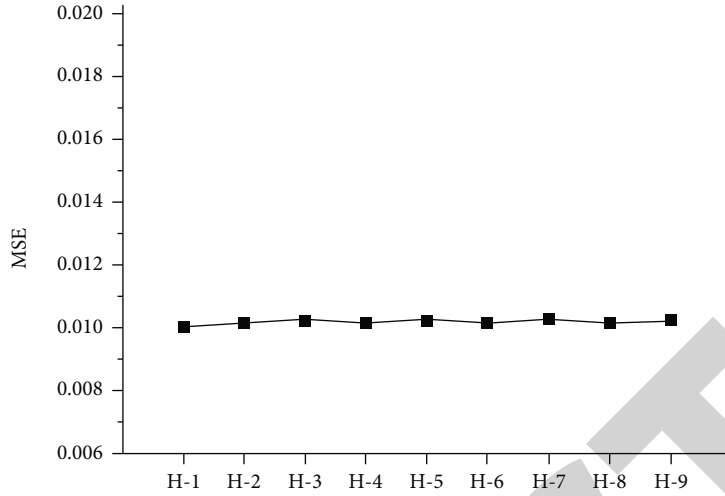| Plan NO.	Enter the data sort order
H-1	$X_{11}X_{12}X_{13}X_{14}X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}X_{41}X_{42}X_{43}X_{44}$
H-2	$X_{44}X_{12}X_{13}X_{14}X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}X_{41}X_{42}X_{43}X_{11}$
H-3	$X_{11}X_{43}X_{13}X_{14}X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}X_{41}X_{42}X_{12}X_{44}$
H-4	$X_{11}X_{12}X_{42}X_{14}X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}X_{41}X_{13}X_{43}X_{44}$
H-5	$X_{11}X_{12}X_{13}X_{41}X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}X_{14}X_{42}X_{43}X_{44}$
H-6	$X_{11}X_{12}X_{13}X_{14}X_{34}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{21}X_{41}X_{42}X_{43}X_{44}$
H-7	$X_{11}X_{12}X_{13}X_{14}X_{21}X_{33}X_{23}X_{24}X_{31}X_{32}X_{22}X_{34}X_{41}X_{42}X_{43}X_{44}$
H-8	$X_{11}X_{12}X_{13}X_{14}X_{21}X_{22}X_{32}X_{24}X_{31}X_{23}X_{33}X_{34}X_{41}X_{42}X_{43}X_{44}$
H-9	$X_{11}X_{12}X_{13}X_{14}X_{21}X_{22}X_{23}X_{31}X_{24}X_{32}X_{33}X_{34}X_{41}X_{42}X_{43}X_{44}$

Figure 10: MSE value of cotton yarn strength of nine input schemes.

Table 7: Selection and input scheme of cotton fiber performance index.

Scheme NO.	Enter the data sort order
J-1	$X_{11}X_{12}\,X_{13}X_{14}X_{21}X_{22}X_{23}X_{24}\,X_{31}X_{32}X_{33}X_{34}X_{41}X_{42}X_{43}X_{44}$
J-2	$0\,X_{12}X_{13}X_{14}X_{21}X_{22}\,X_{23}X_{24}\,X_{31}X_{32}X_{33}X_{34}X_{41}X_{42}X_{43}X_{44}$
J-3	$X_{11}X_{12}\,0\,X_{14}X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}\,X_{41}X_{42}X_{43}X_{44}$
J-4	$X_{11}X_{12}X_{13}0\,X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}X_{41}X_{42}X_{43}X_{44}$
J-5	$X_{11}X_{12}X_{13}X_{14}X_{21}X_{22}X_{23}X_{24}X_{31}0\,X_{33}X_{34}X_{41}X_{42}X_{43}X_{44}$

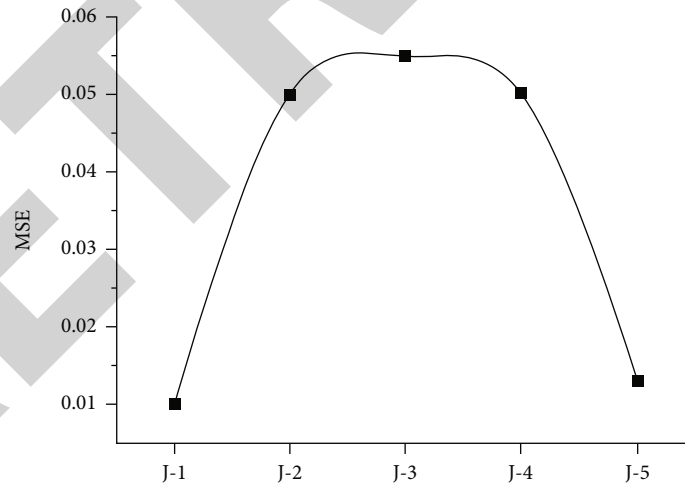
Figure 11: MSE values of six input cotton fiber performance index schemes.

moment of $T + 3$, where I_1^{T+3} is the rotating speed of the rotating cup (r/min).

3.3.6. Output Layer. The output layer is an index of yarn, which can be determined according to the actual situation; in this example, four indexes are determined, namely, yarn strength, yarn Dan Qiang unevenness, yarn evenness unevenness, and total yarn cotton impurities. There are 4 neurons in the output layer.

3.3.7. Experimental Conditions and Main Parameters. The experiment is conducted on the cloud server, and the development language is python3. The data comes from 36.4tex rotor yarn in a cotton mill in Zhejiang. 200 sets of data were collected. Randomly disturb the data set order, and select 90%, i.e., 160 sets of data as training data, 20 sets of data as test data, and 20 sets of data as validation data. Important parameters of network structure are shown in Table 2. It has a convolution layer with 13 convolution kernels and uses the

TABLE 8: Input scheme table for process parameter selection.

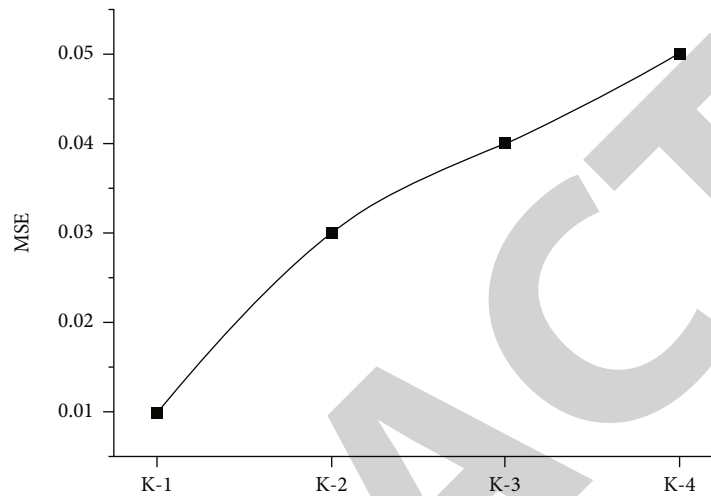| Scheme NO.	Enter the data sort order
K-1	$X_{11}X_{12}X_{13}X_{14}X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}X_{41}X_{42}X_{43}X_{44}$
K-2	$X_{11}X_{12}X_{13}X_{14}X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}X_{41}0\,X_{43}X_{44}$
K-3	$X_{11}X_{12}X_{13}X_{14}X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}X_{41}X_{42}0X_{44}$
K-4	$X_{11}X_{12}X_{13}X_{14}X_{21}X_{22}X_{23}X_{24}X_{31}X_{32}X_{33}X_{34}X_{41}X_{42}X_{43}0$

FIGURE 12: MSE values of four input process parameter index schemes.

TABLE 9: :Four LSTM hidden layer node schemes.

Scheme number	LSTM hidden layer node number
O-1	16
O-2	17
O-3	18
O-4	19

ReLU activation function. It has a pool layer with 12 pool cores. It has a LSTM hidden layer, including 16 nodes. There are 4 nodes in the output layer. The loss function uses MSE. The initial learning rate is 0.01, 100 training times in total.

4. Results and Discussion

4.1. Analysis of Prediction Results. In order to compare the prediction results of yarn quality by CNN-LSTM with the traditional model, the traditional linear regression model and BP neural network are also used for prediction. BP neural network adopts three-layer structure, with 16 neurons as input, 30 neurons as hidden layer, and 4 neurons as output. 20 groups of test data were compared, and MSE was used as evaluation index. The comparison results of the three algorithms are shown in Tables 3 and 4 and Figures 7–9.

As shown in Table 3, the mean absolute error of CNN-LSTM prediction results was 0.080, the mean relative error was 0.008, the mean squared error (MSE) was 0.010, the root-mean squared error (RMSE) was 0.110, and the correla-

tion coefficient squared (R^2) was 0.990 when predicting the strength of rotating cup yarn; the MSE of linear regression model and BP neural network was 0.2 or more; relative to linear regression model and BP neural network, the MSE of CNN-LSTM model has a significant decrease. From Figures 7–9, it can be analyzed that the MSE of CNN-LSTM model is significantly reduced in predicting yarn single-strength unevenness, yarn stem unevenness, and total number of cottons compared to linear regression model and BP neural network. In summary, the CNN-LSTM has higher prediction accuracy than the linear regression model and BP neural network on the rotor yarn dataset with dynamic process data.

4.2. Analysis of Factors Affecting Prediction Accuracy of CNN-LSTM Model

4.2.1. Parameter Setting of CNN-LSTM Model. According to the previous research, the parameters of CNN-LSTM model are set as shown in Table 5, and the following analyses are discussed based on the parameters set in the table.

4.2.2. The Influence of the Order of Input Matrix Eigenvalues on the Model. This section mainly studies the influence of input sequence of eigenvalues on CNN-LSTM model. See Table 6 for the test scheme. The mean square error (MSE) value between the predicted value and the measured value of yarn strength index is used as the evaluation index.

As shown in Figure 10, different input sequences of eigenvalues have no obvious influence on MSE values. That is, the input sequence has no obvious influence on the
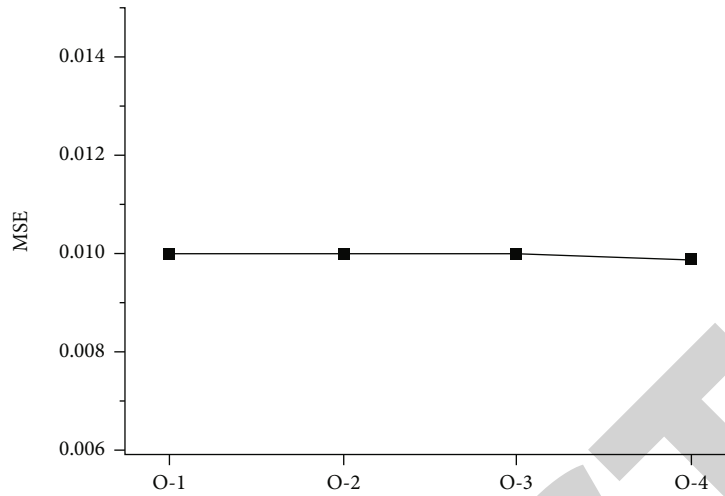
FIGURE 13: MSE diagram of four LSTM hidden layer node schemes.

TABLE 10: Three LSTM layer design schemes.

Scheme NO.	LSTM layers
P-1	1 layer
P-2	2 layer
P-3	Layer 3

prediction accuracy of the model. The main reason is that the deep neural network has automatic adjustment and adaptability to the input value sequence.

4.2.3. The Influence of Cotton Fiber Performance Index on the Model. This section mainly studies the influence of fiber performance index on the prediction accuracy of the model, and look at Table 7 for specific schemes. The mean square error (MSE) value between the predicted value and the measured value of the yarn strength index is used as the evaluation index, and the experimental results are shown in Figure 11.

As shown in Figure 11, when X_{11}, X_{13}, and X_{14} were input to the model with 0 instead, there was a large increase in the MSE value of the model, indicating that these feature values had a large impact on the model prediction accuracy. When X_{32} is not input to the model, although the MSE value also increases, the increase is small, indicating that the impact on the model prediction accuracy is not significant. X_{11}, X_{13}, and X_{14} correspond to the main body length of cotton fiber, the breaking strength of cotton fiber, and the uniformity of cotton fiber fineness, indicating that these feature values have a great impact on the model performance. X_{32} corresponds to the rewetting rate of cotton fiber, indicating that the impact of this feature value on the model performance is not obvious [16–19].

The above results show that different fiber performance indicators have an impact on the prediction accuracy of yarn quality indicators, so when selecting input parameters, it is necessary to combine relevant practical experience with the actual situation, that is, different raw material attributes.

4.2.4. Influence of Rotor Spinning Process Parameters on the Model. This section mainly studies the influence of process parameters on the model. According to the idea of zeroing one process parameter at a time, see Table 8 for the specific scheme.

Figure 12 shows that the process parameters have a significant impact on the prediction accuracy of the CNN-LSTM model, with X_44 (rotating cup speed) having the most pronounced effect. This indicates that the process parameters, especially some critical ones, have a large impact on the yarn quality.

4.2.5. Selection of LSTM Hidden Layer Node Number. The number of LSTM hidden layer nodes cannot be less than the eigenvalue of the input LSTM layer, that is, 16 nodes. Add one hidden layer node at a time until the end of 19 nodes. Four experimental schemes are designed, as shown in Table 9.

As shown in Figure 13, 16 nodes, 17 nodes, 18 nodes, and 19 nodes are set for LSTM according to experience. When set to 19 nodes, the MSE value decreases slightly. Considering that 19 nodes are larger than 16 nodes in calculation amount and time, 16 nodes are selected in this neural network model.

4.2.6. Influence of LSTM Layer Number on Model. The design idea of LSTM layers is to increase the number of LSTM layers under the condition of 16 nodes in each layer and observe the influence on the model accuracy. A total of three schemes are designed as shown in Table 10.

As shown in Figure 14, when predicting yarn strength, one layer of LSTM, two layers of LSTM, and three layers of LSTM were used, and the MSE value decreased only slightly. From the point of view of reducing computation, computing time, and saving resources, this model chooses one-layer LSTM [20–22].

4.2.7. Influence of Optimization Algorithm on Model. CNN-LSTM model is special, and the gradient descent optimization algorithm with fixed learning rate is not ideal, and it
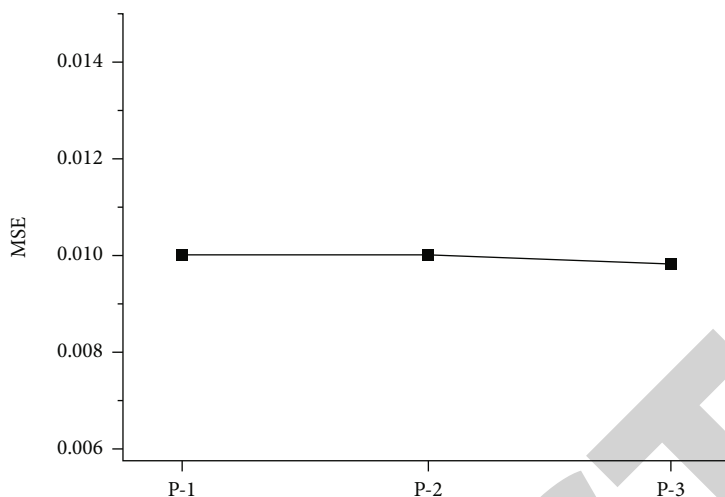
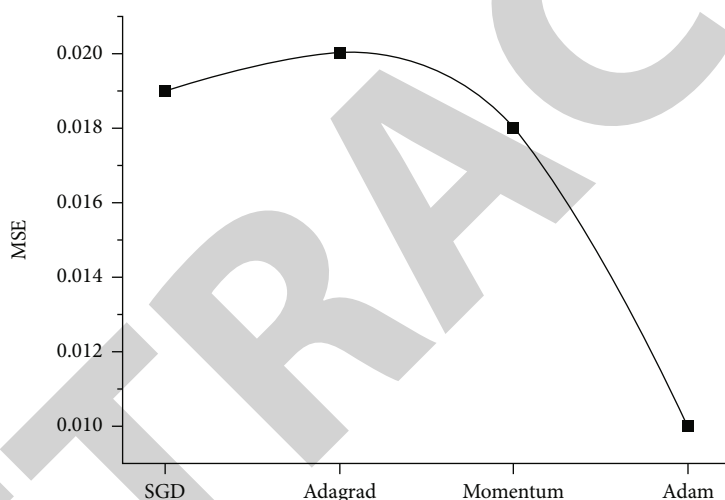Figure 14: Relationship between LSTM layer number and MSE diagram.

Figure 15: Relationship between optimization algorithm and MSE.

needs Adam algorithm, that is, adaptive learning rate to optimize. The following four optimization algorithms are selected for comparative study, which are SGD, Adagrad, Momentum, and Adam optimization algorithms. These four optimal algorithms have their own characteristics, SGD (Stochastic Gradient Descent) trains for large samples; Adagrad (Adaptive Gradient Algorithm) is an improvement of SGD to improve its robustness; Momentum is also an improvement on SGD, which can accelerate the convergence of SGD and has a strong inhibition on convergence oscillation; Adam (Adaptive Moment Estimation) only needs to give an initial learning rate, and can adapt the learning rate according to the situation in the training process [23, 24].

As shown in Figure 15, four optimization algorithms are used for experiments; when Adam optimization algorithm is used, the MSE value of yarn strength reaches the lowest, that is, the prediction accuracy reaches the highest. The reason is that CNN-LSTM model cannot be trained with a fixed learning rate, and it needs to adjust the learning rate according to the training situation; Adam just meets this requirement and

can automatically adjust the learning rate. To sum up, Adam optimization algorithm is the best optimization algorithm for CNN-LSTM model.

5. Conclusions

The method mentioned in the literature can clearly determine the relationship between the input fiber, the original eigenvalue of the process, and the final yarn quality, but the prediction accuracy is low. Because spinning is a complex process, it is difficult to express the relationship between the original characteristic value of fiber and process and the final yarn quality with a definite formula according to human thinking habits.

This paper aims to improve the accuracy of yarn quality prediction. From the perspective of processing time sequence, CNN-LSTM deep neural network model based on time sequence is designed. The following conclusions can be drawn through experiments:

(1) Compared with the traditional yarn prediction method, CNN-LSTM has higher prediction correctness

(2) The production process and its parameters have a great influence on the prediction correctness

(3) Different optimization algorithms have great influence on the model

Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The author declares that there is no conflict of interest with any financial organizations regarding the material reported in this manuscript.

Acknowledgments

References

[1] C. Gao, C. Yu, J. Wang, and W. Yu, "Study on prediction model of cotton performance index on yarn quality," *Cotton Textile Technology*, vol. 20, no. 8, pp. 18–22, 2016.

[2] L. S. Admuthe and S. Apte, "Adaptive neuro-fuzzy inference system with subtractive clustering: a model to predict fiber and yarn relationship," *Textile Research Journal*, vol. 80, no. 9, pp. 841–846, 2010.

[3] H. Akbilgic and J. A. Howe, "Symbolic pattern recognition for sequential data," *Sequential Analysis*, vol. 36, no. 4, pp. 528–540, 2017.

[4] A. E. Amin, "A novel classification model for cotton yarn quality based on trained neural network using genetic algorithm," *Knowledge-Based Systems*, vol. 39, pp. 124–132, 2013.

[5] J. Donahue, L. A. Hendricks, M. Rohrbach et al., "Long-term recurrent convolutional networks for visual recognition and description," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 4, pp. 677–691, 2017.

[6] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[7] L. Gui, *Research on Prediction and Inversion Model in Virtual Processing of Fine Wool Textiles*, Donghua University, doctoral dissertation, Shanghai, 2010.

[8] C. Dongsheng, J. Peiwu, and S. Xuehui, "Grey dominance analysis of flax fiber quality and yarn quality," *Journal of Textiles*, vol. 23, no. 7, 331 pages, 1992.

[9] S. Chuping, C. Binbin, and L. Shaoqin, "Research on Intelligent Optimization of yarn production process based on SVM," *Wool Spinning Technology*, vol. 43, no. 7, pp. 13–17, 2015.

[10] W. Kanfeng, L. Kai, and H. Xiubao, "Prediction of combed wool yarn based on neural network," *Journal of Donghua University*, vol. 31, no. 1, pp. 66–70, 2005.

[11] Z. Wei, *Research on Fabric Component Classification Algorithm Based on Deep Learning*, Zhejiang University of Technology, Master's Thesis, 2019.

[12] J. Schmidhuber, *Gradient Flow in Recurrent Nets: The Difficulty of Learning Long-Term Dependencies*, Wiley-IEEE Press, 2001.

[13] J. Wang and H. Xiubao, "Study on rotor spinning knitting yarn technology (I)," *Modern Textile Technology*, vol. 15, no. 1, pp. 1–3, 2007.

[14] T. Y. Kim and S. B. Cho, "Predicting residential energy consumption using CNN-LSTM neural networks," *Energy*, vol. 182, pp. 72–81, 2019.

[15] Y. Yu, X. Si, C. Hu, and J. Zhang, "A review of recurrent neural networks: LSTM cells and network architectures," *Neural Computation*, vol. 31, no. 7, pp. 1235–1270, 2019.

[16] J. Zhao, J. Huang, D. Zhi et al., "Functional network connectivity (FNC)-based generative adversarial network (GAN) and its applications in classification of mental disorders," *Journal of Neuroscience Methods*, vol. 341, p. 108756, 2020.

[17] A. W. Freeman, "A model for the origin of motion direction selectivity in visual cortex," *Journal of Neuroscience*, vol. 41, no. 1, pp. 89–102, 2021.

[18] F. El-Habiby and R. El-Bealy, "Fractional factorial treatment of ring spun yarn quality (Dept.T)," *MEJ Mansoura Engineering Journal*, vol. 21, no. 4, pp. 1–15, 2021.

[19] B. Birlie and S. Rangaraj, "Investigation of yarn quality in ring yarn by modifying bottom apron/nose bar with perforations and air-suction," *American Journal of Applied Scientific Research*, vol. 7, no. 3, p. 56, 2021.

[20] A. B. Abdulghafour, S. H. Omran, M. S. Jafar, M. M. Mottar, and O. H. Hussein, "Application of statistical control charts for monitoring the textile yarn quality," *Journal of Physics: Conference Series*, vol. 1973, no. 1, p. 012158, 2021.

[21] P. Li, M. Guo, F. Sun, and W. Gao, "An adhesive-aided ring spinning for improving cotton yarn quality with the aid of sodium carboxymethyl cellulose solution," *Journal of Engineered Fibers and Fabrics*, vol. 15, p. 155892502092783, 2020.

[22] A. Eg, A. Ek, and B. Ae, "Yarn tensile properties modeling using artificial intelligence," *Alexandria Engineering Journal*, vol. 59, no. 6, pp. 4435–4440, 2020.

[23] B. Sarker and S. Chakraborty, "Discriminant analysis-based modeling of cotton fiber and yarn properties," *Research Journal of Textile and Apparel*, vol. 10, no. 7, 2022.

[24] K. N. Chatterjee, D. Sharma, and H. Pal, "Quality aspects of sustainable handloom denim fabrics made of hand spun and machine spun cotton yarn," *Journal of Textile and Apparel, Technology and Management*, vol. 11, no. 2, 2020.