CHAPTER-6

Wheat Crop Yield Production Analysis using GATE-NN and Spiking-NN

6.1 Introduction

In this chapter, SNN [78] was implemented using a single spatial feature i.e.: NDVI and the results and performance were found based on various evaluation parameters. The results obtained were then compared with GATE-NN results. In order to improvise the performance of SNN, it was then implemented using the three feature vectors, i.e.; NDVI, VCI, and SPI; these values were passed for training as the input features in SNN [78], and the results obtained were then compared with GATE-NN results obtained for three feature values.

Most existing SNN training algorithms include the BP works focus on FF networks. The Spiking neural networks (SNNs), are an important class of SNNs and are especially competent for processing temporal signals such as time series and speech data [7].

6.2 Spiking Neural Networks

The idea for the presentation of the first SNN [78] computational model was for crop yield estimation [11] from standardized vegetation record. It exhibits the advancement and testing of a methodological structure which uses the spatial gathering of time arrangement of Moderate Resolution Imaging Spectro radiometer 250-m determination information and recorded product yield information to train a SNN and make promising expectation of crop yield.

6.3 Spiking Neuron Model [58]

The basic assumption underlying the implementation of spiking neuron models is the timing of spikes rather than the specific shape of spikes that carries neural information. Spiking neurons [33] and the adaptive synapses between neurons contribute to a recent approach in decision making, cognition and learning.

The unit of the SNN is the neuron, which is created to be the one similar to biological. This neuron processes the information that had arrived from the pre-synaptic neurons (PrSyN) and it sends the train of spikes (sequence of spikes) to the postsynaptic neurons (PoSyN) through the axon. The probability that the neuron will fire increases with the increasing of the membrane potential: here we say that a spike is to be generated, only if the membrane potential reaches a threshold (called spike threshold [61]).

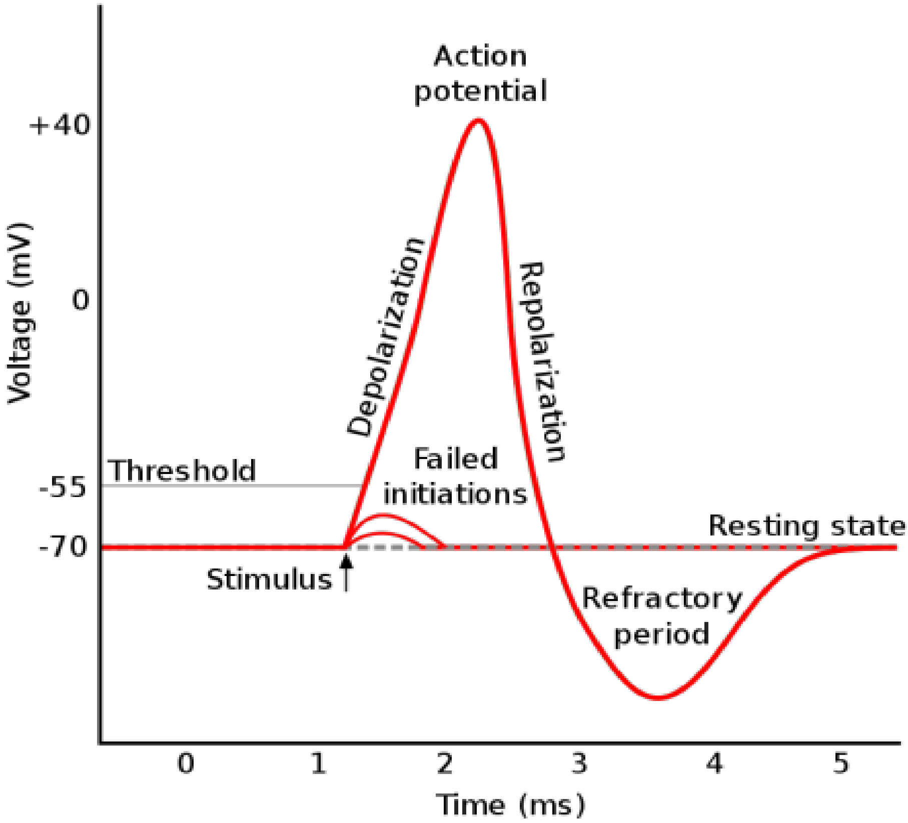

Figure 6.1: Representation of an action potential [25]

Figure 6.1 shows the approximative plotting of the spike of a neuron. The depolarization occurs when the input stimulus is higher enough to reach the spike threshold. When this happens, the action potential rises and, until the ending of the repolarization, the neuron is in the absolute refractory period, in which it cannot fire again and when the repolarization state gets over by the crossing of the resting potential, the hyperpolarization starts where it is more difficult that the neuron fires, but it is possible. This time period is called relative refractory period. In the end, the cell returns to resting potential.

Some of the neuron models are as mentioned below:

i. Hodgking-Huxley (HH)

ii. Leaky integrate-and-fire (LIF)

iii. Spike response (SRM)

iv. Izhikevich neuron (IZK)

In this work we have used the LIF neuron model as taken in the previous work [78].

6.3.1 Components of SNN

Leaky Integrate and Fire (LIF) [57] neurons (Dayan and Abbott, 2001) and plastic synapses are fundamental and biologically plausible computational elements for emulating the dynamics of SNNs. The sub-threshold dynamics of a LIF spiking neuron can be formulated as eq. (46).

$$\tau_m \frac{dV_{mem}}{dt} = -V_{mem} + I(t) \tag{46}$$

where; V_{mem} is the post-neuronal membrane potential and τ_m is the time constant for membrane potential decay. The input current, $I(t)$, is defined as the weighted summation of pre-spikes at each time step as given below in eq. (47).

$$I(t) = \sum_{i=1}^{n^l} (\left(w_i \sum_k) \theta_i (t - t_k) \right) \tag{47}$$

where; n^l indicates the number of pre-synaptic weights, w_i is the synaptic weight connecting ith pre-neuron to post-neuron. $\theta_i(t - t_k)$ is a spike event from ith pre-neuron at time t_k, which can be formulated as a Kronecker delta function as follows in eq. (48).

$$\theta(t-t_k)=1, \text{ if } t=t_k \text{ or is equal to 0, otherwise} \tag{48}$$

where; t_k is the time instant that kth spike occurred. Figure 6.2 illustrates LIF neuronal dynamics. The impact of each pre-spike, $\theta_i(t - t_k)$, is modulated by the corresponding synaptic weight (w_i) to generate a current influx to the post-neuron. Note, the units do not have bias term. The input current is integrated into the post-neuronal membrane potential

(V_{mem}) that leaks exponentially over time with time constant (τ_m). When the membrane potential exceeds a threshold (V_{th}), the neuron generates a spike and resets its membrane potential to initial value. The Figure6.2 gives the illustration of LIF neuron dynamics.

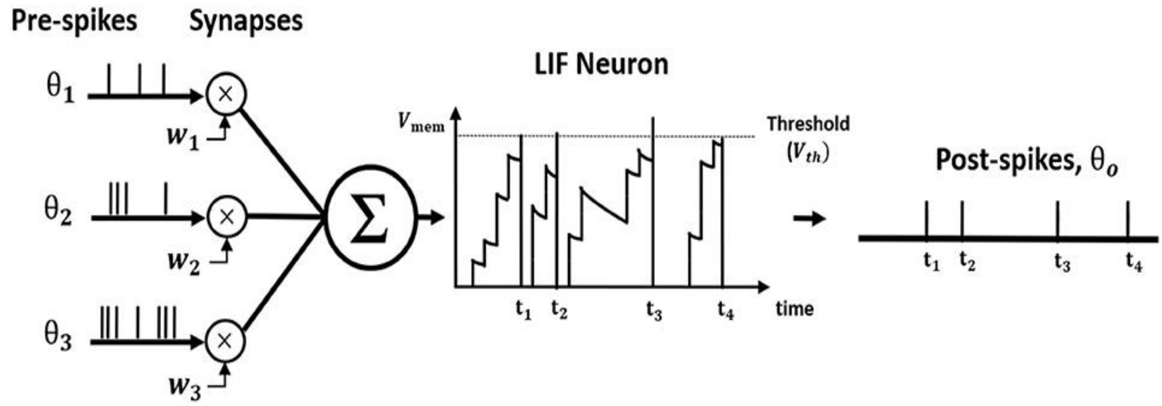

Figure 6.2: Leaky integrate-and-fire [78]

Table 6.1 Lists the annotations used in Equations

Notations	Meaning
θ	Spike event
x	The sum of pre-spike events over time
w	Synaptic weight
V_{mem}	Membrane potential
V_{th}	Neuronal firing threshold
I	Input current at each time step
net	Total current influx over time
a	Activation of spiking neuron
E	Loss function
δ	Error gradient

6.4 SNN for Crop Yield Prediction

In this work for predicting the crop yield production for the study years, a three layered SNN having small number of neurons as well as small number of synapses was designed, then this NN learns to classify and predicts the crop yield production. The weight adaptation and pattern recognition in a time and in an efficient manner for achieving the goal is obtained by training and testing algorithms. The SNN provides a robust solution for the mentioned challenge in three steps.

In the first or initial step, the digital image was converted into spike trains, so that, each spike becomes a discriminative candidate of a row pixel in the image.

In the next step; in order to reduce the network size and to mimic human perception of the image, the spike trains were incorporated into few sections. Here, every output spike specifies a part of the image in the row order.

In the last and the third step, the training layer involves learning, output spike firing, and Winner-Take-All network (WTA) [78]. Furthermore, the results obtained are then compared with the statistical data to predict the wheat crop yield in similar situations.

6.5 Diagrammatic Explanation of SNN

The architecture of SNN is shown as in Figure 6.3, which basically includes the three components, first is a neural spike generator, second is the segmentation of image, and third is the learning phase and output pattern generation. The brief and implementation process are being explained further.

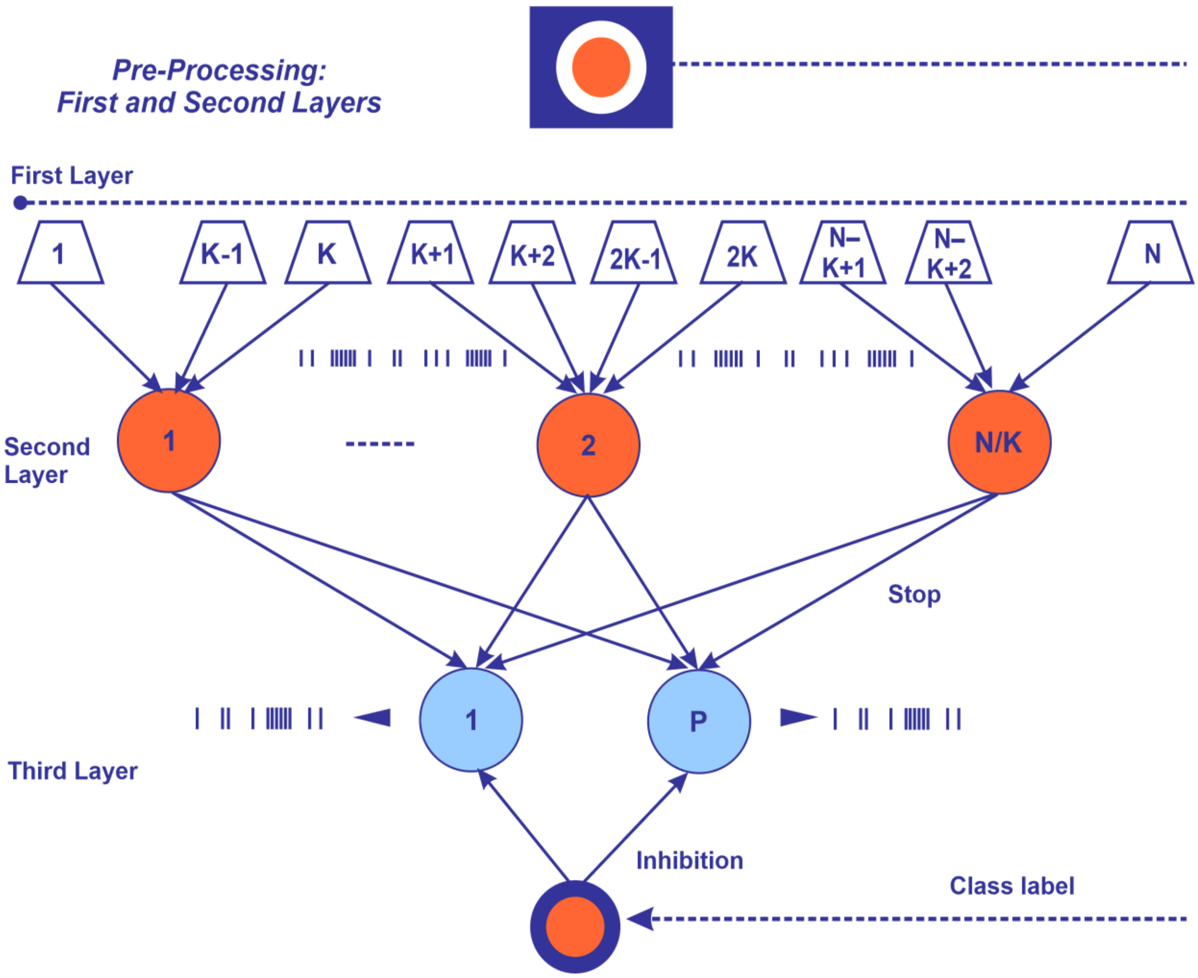

Figure 6.3. Supervised SNN Architecture [1]

Figure 6.3 represents the supervised SNN architecture containing spike transcription layer, spike train segmentation, STDP learning, output pattern firing, and inhibitory neuron. N: number of rows. K: number of adjacent rows connected to one neuron. P: number of classes. Black circle inhibits all output neurons except the one designated by the class label.

6.6 Yield Prediction of Wheat Crop in the Selected Region Performed using SNN [78].

Initialization of Pre and Post Synaptic of SNN

As each neuron connects through the next neuron by a junction which is term as synapses. So, incoming signals are initially passed through the pre-synaptic (P_{rs}) area and then postsynaptic (P_{os}) junction make changes in input signal [2, 82]. So, evaluation of these values was done by eq. (49) and eq. (50).

$$P_{rs}(t) = \int_0^\infty K_{syn}\left(t - t^f\right)e^{\frac{-t}{\tau}} \tag{49}$$

where; K_{syn} is the pre-synaptic spike train, Key controls the peak conductance value, t is a range of time firing instance and τ is the synaptic time constant. In this work infinity is nothing but the input vectors for training.

This formula performs linear spatiotemporal summation across the received spike train. The total postsynaptic current is obtained by eq. (50).

$$P_{os}(t) = \int_0^\infty P_{os}(t) - V(t)\int_0^\infty P_{os}(t) \tag{50}$$

The weight of the neurons is initialized by below eq. (51), where each neuron was considered as vertex and synapses were considered as the edge between them, here input is spikes of neural network.

$$w_{ij}(t) = a_o + a_1P_{rs}(t) + a_2P_{os}(t) + a_3P_{rs}(t)P_{os}(t) + a_4P_{rs}(t)P_{os}(t) \tag{51}$$

In above eq. (51), $w_{ij}(t)$ is the weight between i^{th} and j^{th} layers and a_0, a_1, a_2, a_3 and a_4 are coefficient constant to manage the changing rate of synapses.

Steps for finding out the desired output:

a. Consider a three-layered ANN.

b. Now considering; ‘i’ as the input layer of the network, while ‘j’ is considered as the hidden layer of the network and ‘k’ is considered as the output layer of the network.

c. If w_{ij} represents a weight of the between nodes of different consecutive layers.

d. Then, the output (D) of the layer depends on the below eq. (52)

$$X_j = \sum x_i . w_{ij} b_j \tag{52}$$

where, $1 \leq i \leq n$; and n is the number of inputs x_i to node j, and b_j is the biasing for node j.

e. Desired output D is then passed to check the learning process and the Error is found by using the eq. (53).

$$E = D\text{-sum}(X) \tag{53}$$

f. The weight Adjustment is done by below eq. (54).

$$w_{ij} = w_{ij} * \text{rand}\ () \tag{54}$$

Now, by repeating the above steps and adjusting the values of error obtained, the final output was found.

6.7 Predicting wheat crop yield production using SNN and GATE-NN applying NDVI single feature value.

SNN was implemented in MATLAB and the results were found on various parameters as in [78]. The result obtained was then compared with GATE-NN.

Table 6.2 Experimental Results obtained from SNN and GATE-NN using single feature- NDVI

SNN [78]						
Year	**2014-15**	**2015-16**	**2016-17**	**2017-18**	**2018-19**	**2019-20**
Field Truth Value (in Metric Tonnes)	**17103.9**	**17688.67**	**17939.33**	**15910.79**	**16520**	**19610**
YIELD	18260.51	20180.13	10708.96	14936.87	11993.99	16340.89
RMSE	4006.108	3162.4	8812.465	3092.22	6908.518	4925.903
RE	6.762249	14.08505	40.30459	6.121098	27.39716	16.67062
ACCURACY	93.23775	85.91495	59.69541	93.8789	72.60284	83.32938
TIME	0.001052	0.000977	0.000957	0.000959	0.001047	0.00108
GATE-NN						
Year	**2014-15**	**2015-16**	**2016-17**	**2017-18**	**2018-19**	**2019-20**
Field Truth Value (in Metric Tonnes)	**17103.9**	**17688.67**	**17939.33**	**15910.79**	**16520**	**19610**
YIELD	16060.47	15645.27	15275.11	15399.62	15295.96	15078.27
RMSE	3316.854	1888.71	14530.09	10595	12341.45	8700.178
RE	6.100558	11.55205	14.85127	3.212711	7.40947	23.1093
ACCURACY	93.89944	88.44795	85.14873	96.78729	92.59053	76.8907
TIME	0.255283	0.254226	0.086669	0.170759	0.105569	0.197477

6.7.1 Comparison between SNN and GATE-NN in terms of prediction of wheat crop production in Metric Tonnes using single feature

Table 6.3: Comparison between SNN and GATE-NN in terms of wheat crop yield prediction in Metric Tonnes using single feature

S. No.	Years	Ground Value	SNN [76]	GATE-NN
1	2014-2015	17103.9	18260.508	16060.467
2	2015-2016	17688.67	20180.126	15645.267
3	2016-2017	17939.33	10708.955	15275.111
4	2017-2018	15910.79	14936.873	15399.622
5	2018-2019	16520	11993.988	15295.956
6	2019-2020	19610	16340.891	15078.267

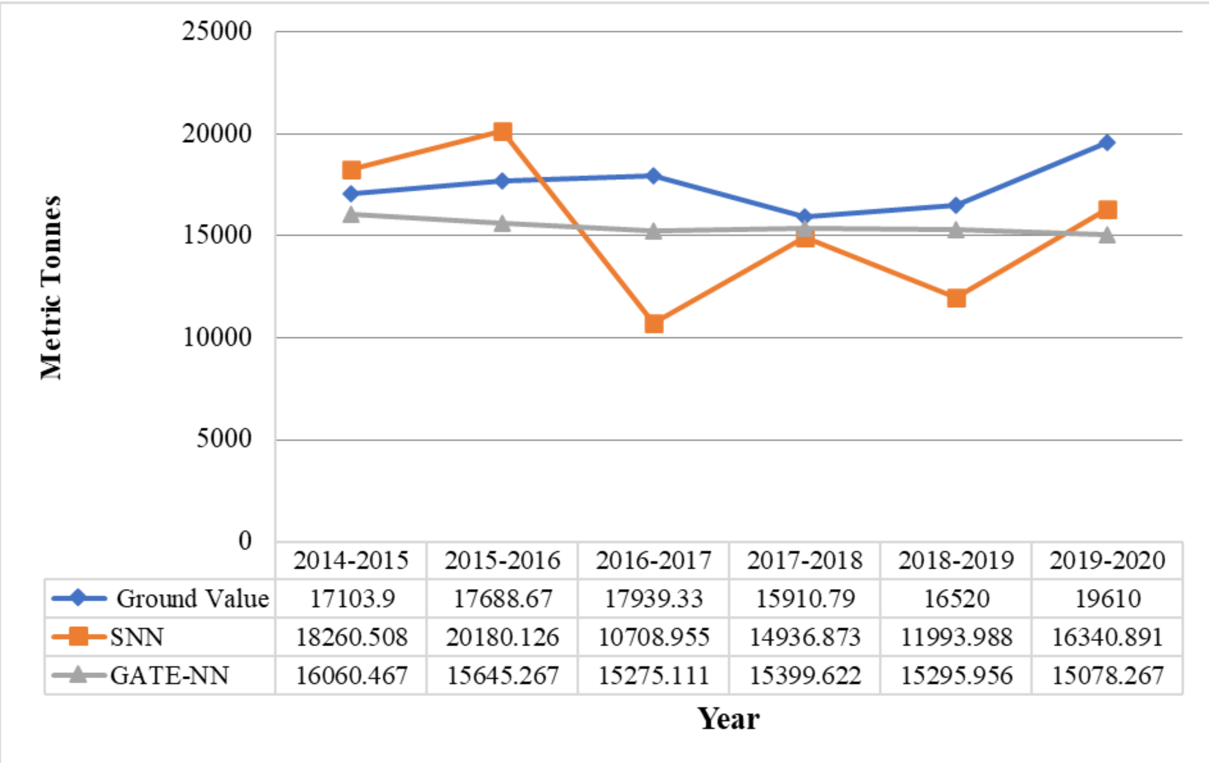

Figure 6.4: Comparison between SNN and GATE-NN in terms of wheat crop yield prediction using single feature

It has been observed by table 6.3 and figure 6.4 that through proposed work; GATE-NN the prediction of wheat crop yield production using single feature- performs well as compared to SNN. In this research work GATE-NN uses TLBO and GA algorithms for reducing input size of data and EBP neural network, which is responsible for increasing the value of prediction accuracy in comparison to SNN.

6.7.2 Comparison between SNN and GATE-NN in terms of RMSE using single feature

Table 6.4: Comparative table between SNN and GATE-NN in terms of RMSE using single feature

S. No.	Year	SNN [1]	GATE-NN
1	2014-2015	4006.108	3316.854
2	2015-2016	3162.400	1888.710
3	2016-2017	8812.465	14530.088
4	2017-2018	3092.220	10594.999
5	2018-2019	6908.518	12341.453
6	2019-2020	4925.903	8700.178

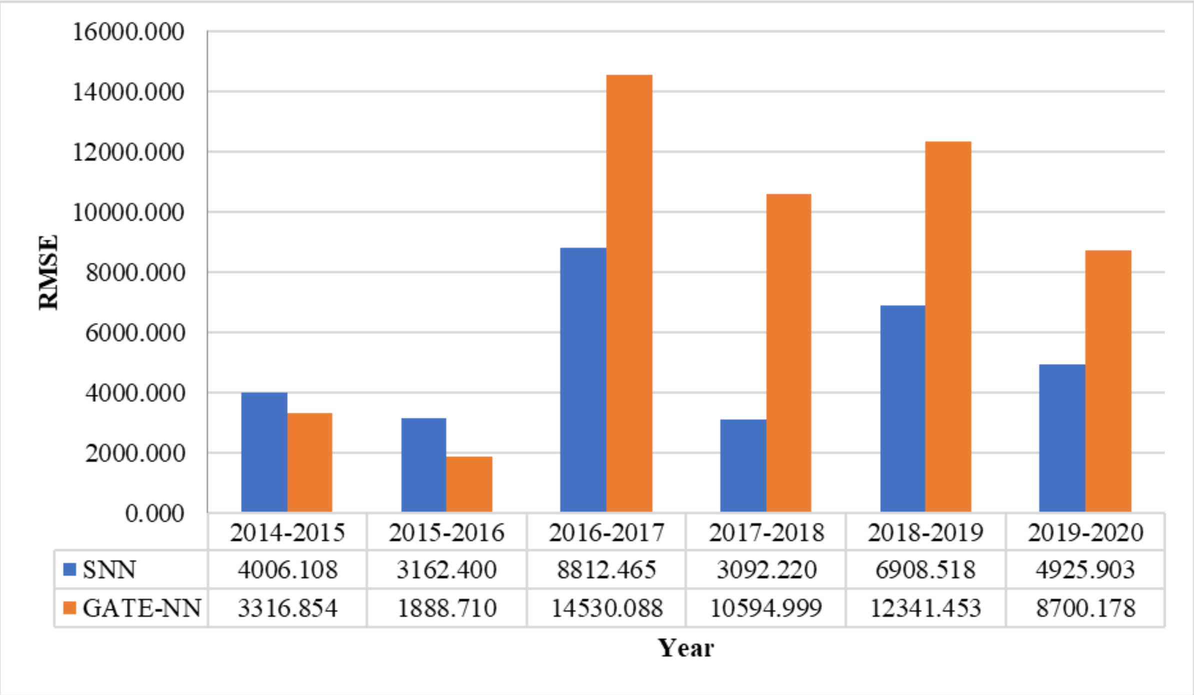

Figure 6.5: Comparison between SNN and GATE-NN in terms of RMSE using single feature

It has been observed from table 6.4 and figure 6.5, that the proposed work GATE-NN of crop yield prediction using single feature value does not performed better as compared to SNN expect for year 2014-15 and 2015-16.

6.7.3 Comparison between SNN and GATE-NN in terms of RE using single feature

Table 6.5: Comparative table between SNN and GATE-NN in terms of REusing single feature

S. No.	Year	SNN [7]	GATE-NN
1	2014-2015	6.762	6.101
2	2015-2016	14.085	11.552
3	2016-2017	40.305	14.851
4	2017-2018	6.121	3.213
5	2018-2019	27.397	7.409
6	2019-2020	16.671	23.109

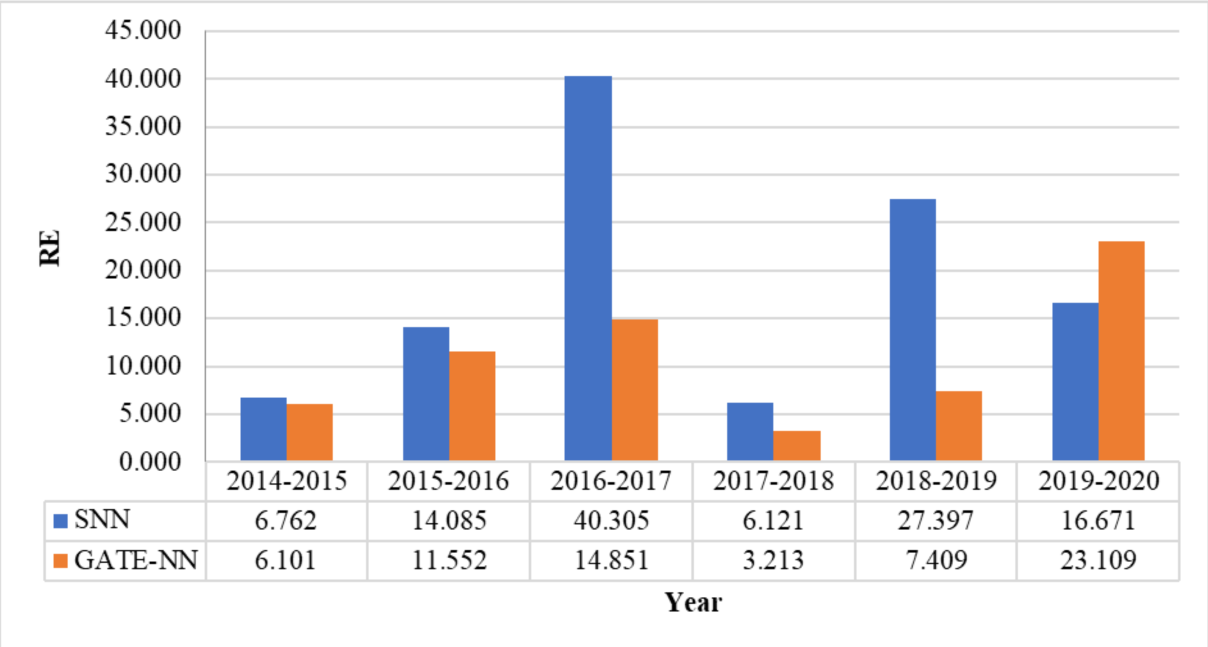

Figure 6.6: Comparison between SNN and GATE-NN in terms of RE using single feature

From the table 6.5 and figure 6.6, it is seen, that the relative error of GATE-NN for crop yield prediction work using single feature value is lesser as compared SNN expect for the year 2019-20. So, it shows that combination of two soft computing approaches first was combination of TLBO with GA and other was EBP-NN has reduced the Relative Error value in GATE-NN in comparison to SNN.

6.7.4 Comparison between SNN and GATE-NN in terms of Prediction Accuracy obtained using single feature

Table 6.6: Comparison between SNN and GATE-NN in terms of Accuracy obtained in % using single feature

S. No.	Year	SNN [78]	GATE- NN	Improvement comparison in Percentage from SNN to GATE-NN
1	2014-2015	93.238%	93.899%	0.704%
2	2015-2016	85.915%	88.448%	2.864%
3	2016-2017	59.695%	85.149%	29.893%
4	2017-2018	93.879%	96.787%	3.005%
5	2018-2019	72.603%	92.591%	21.587%
6	2019-2020	83.329%	76.891%	-8.373%
			Average	8.107%

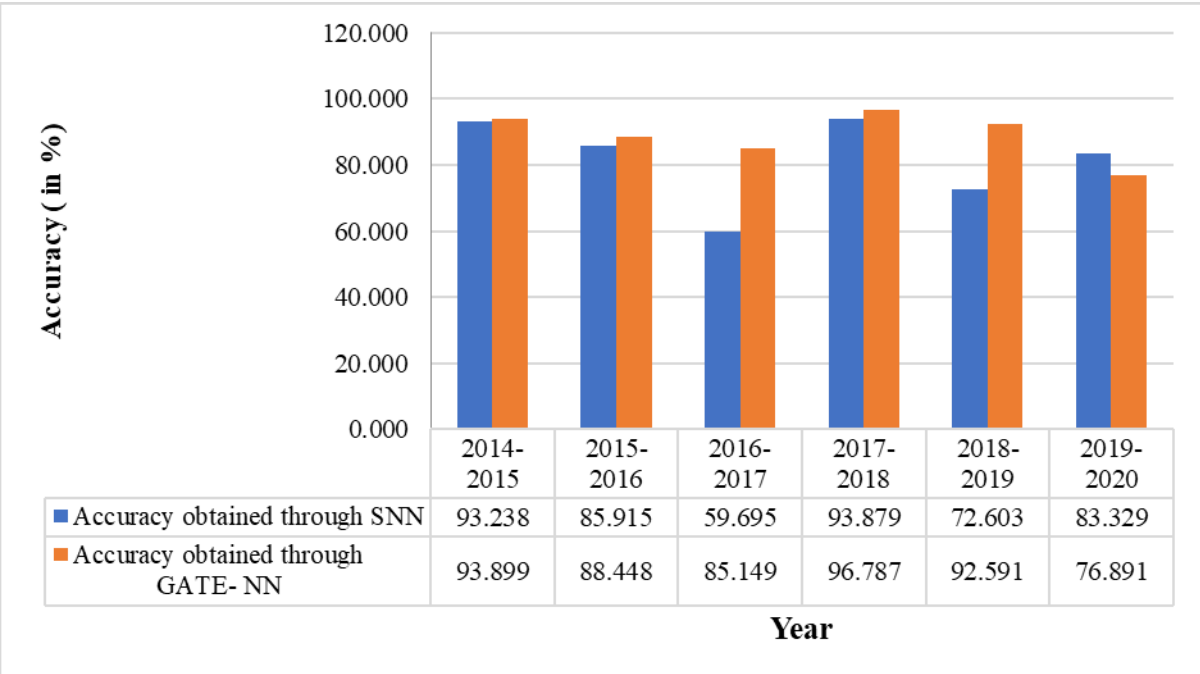

Figure 6.7: Comparison between SNN and GATE-NN in terms of Accuracy obtained using single feature

From the table 6.6 and figure 6.7, it is seen, that using three feature values, the prediction accuracy obtained by GATE-NN for crop yield prediction is higher as compared SNN. So, it is obtained that combination of two soft computing approaches first was TLBO and other was EBP-NN has high accuracy of prediction percentage through GATE-NN in comparison to SNN.

6.7.5 Comparison between SNN and GATE-NN in terms of Training Time using single feature.

Table 6.7: Comparison between SNN and GATE-NN in terms of Training Time using single feature

S. No.	Year	SNN [7]	GATE-NN	Difference in training time between GATE-NN and SNN
1	2014-2015	0.00105	0.255	0.25395
2	2015-2016	0.00098	0.254	0.25302
3	2016-2017	0.00096	0.087	0.08604
4	2017-2018	0.00096	0.171	0.17004
5	2018-2019	0.00105	0.106	0.10495
6	2019-2020	0.00108	0.197	0.19592
	Average	**0.00102 secs**	**0.18114 secs**	**0.18012 secs**

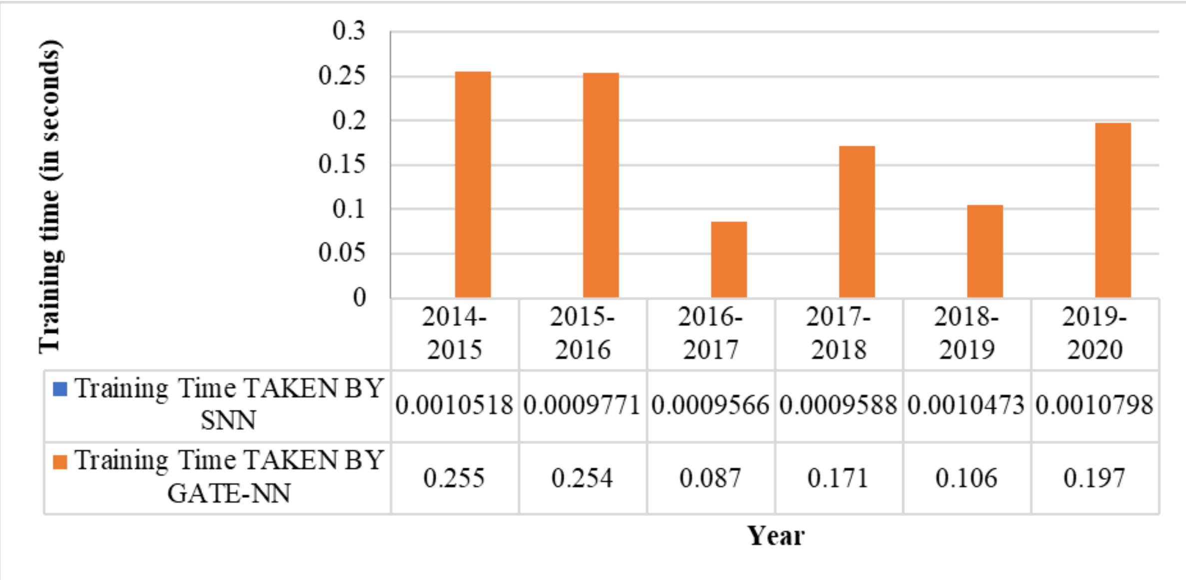

Figure 6.8: Comparison between SNN and GATE-NN in terms of Training Time using single feature

It has been observed by table 6.7 and figure 6.8 that by using three feature values, the training time required for GATE-NN was comparatively more than SNN.

6.8 Predicting wheat crop yield production using SNN and GATE-NN applying three geo spatial features- NDVI, VCI and SPI.

Results obtained after the implementation of SNN and GATE-NN ran on the dataset for three features- NDVI, VCI, SPI can be seen in below tables and graphs.

6.8.1 Comparison of results obtained from SNN and GATE-NN using three features' values (NDVI, VCI, SPI)

Table 6.8: Experimental Results obtained from implemented models using three features- NDVI, VCI, SPI

SNN [78]						
Year	**2014-15**	**2015-16**	**2016-17**	**2017-18**	**2018-19**	**2019-20**
Ground Value (in Metric Tonnes)	**17103.9**	**17688.7**	**17939.3**	**15910.8**	**16520**	**19610**
YIELD	13303.97	17123.6	11836.5	12661.7	12070.5	13010.5
RMSE	3887.299	1454.13	6197.3	3308.97	4571.13	6648.18
RE	22.21673	3.1947	34.0191	20.4207	26.9342	33.6538
ACCURACY	77.78327	96.8053	65.9809	79.5793	73.0658	66.3462
TIME	0.006046	0.00645	0.00637	0.00628	0.00583	0.0058
GATE-NN						
Year	**2014-15**	**2015-16**	**2016-17**	**2017-18**	**2018-19**	**2019-20**
Ground Value (in Metric Tonnes)	**17103.9**	**17688.7**	**17939.3**	**15910.8**	**16520**	**19610**
YIELD	17049.33	17120.9	16787.2	16921.9	17355.7	16813.5
RMSE	542.5904762	567.739	973.118	1336.07	1313.74	2384.83
RE	0.319030552	3.20963	6.42255	6.3546	5.0588	14.2608
ACCURACY	99.68096945	96.7904	93.5774	93.6454	94.9412	85.7392
TIME	0.2382486	0.24012	0.0684	0.15192	0.10271	0.18668

6.8.2 Comparison between SNN and GATE-NN in terms of wheat yield prediction using three features

Table 6.9: Comparison between SNN and GATE-NN in terms of wheat crop yield prediction in Metric Tonnes using three features

S. No.	Years	Ground Value	SNN [76]	GATE-NN
1	2014-2015	17103.9	13303.972	17049.33333
2	2015-2016	17688.67	17123.569	17120.92857
3	2016-2017	17939.33	11836.532	16787.16667
4	2017-2018	15910.79	12661.701	16921.85714
5	2018-2019	16520	12070.472	17355.71429
6	2019-2020	19610	13010.484	16813.45238

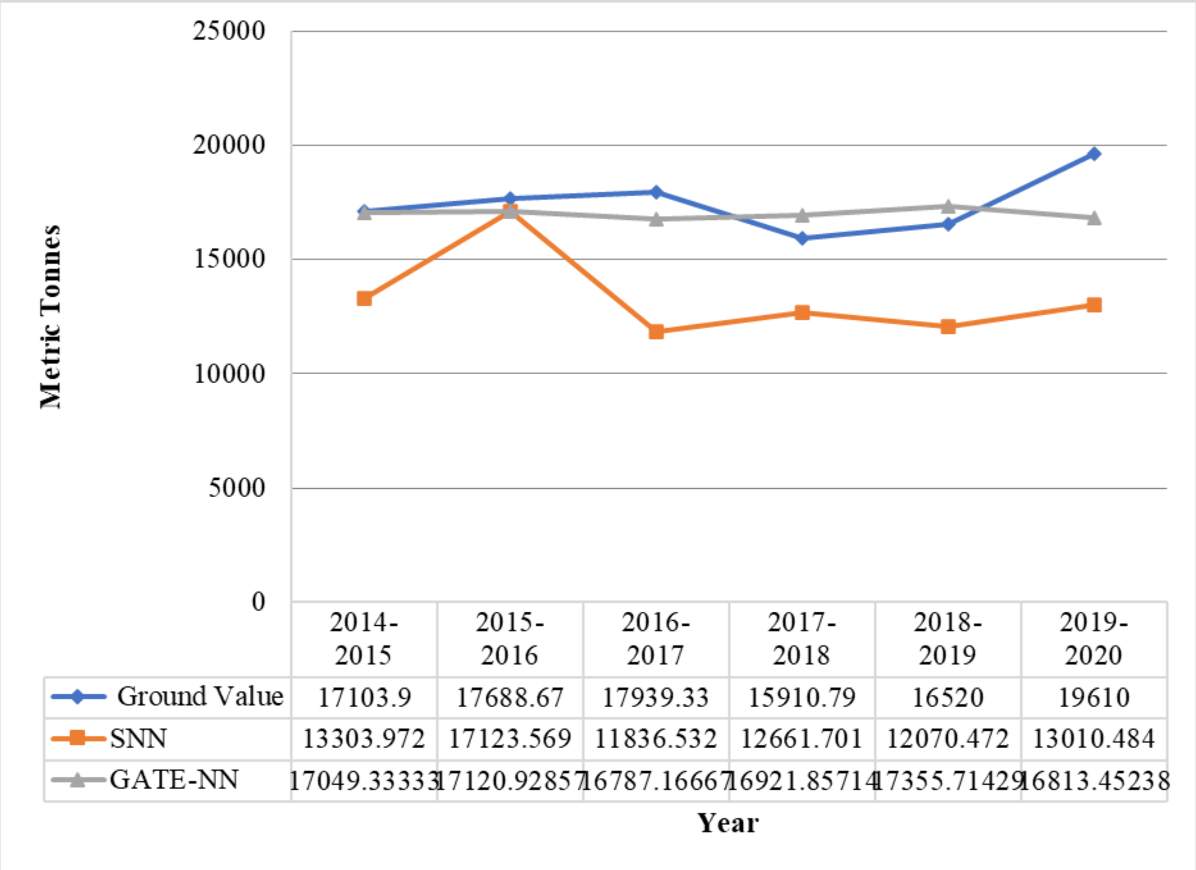

Figure 6.9: Comparison between SNN and GATE-NN in terms of yield prediction using three features

It has been observed by table 6.9 and figure 6.9 that through proposed work; GATE-NN the prediction of wheat crop yield production using three feature values- performs well as compared to SNN. In this research work GATE-NN uses TLBO and GA algorithms for reducing input size of data and EBP neural network, which is responsible for increasing the value of prediction accuracy in comparison to SNN.

6.8.3 Comparison between SNN and GATE-NN in terms of RMSE using three features

Table 6.10: Comparison between SNN and GATE-NN in terms of RMSE using three features

S. No.	Year	SNN [1]	GATE-NN
1	2014-2015	3887.299	542.590
2	2015-2016	1454.125	567.739
3	2016-2017	6197.301	973.118
4	2017-2018	3308.97	1336.072
5	2018-2019	4571.132	1313.736
6	2019-2020	6648.181	2384.834

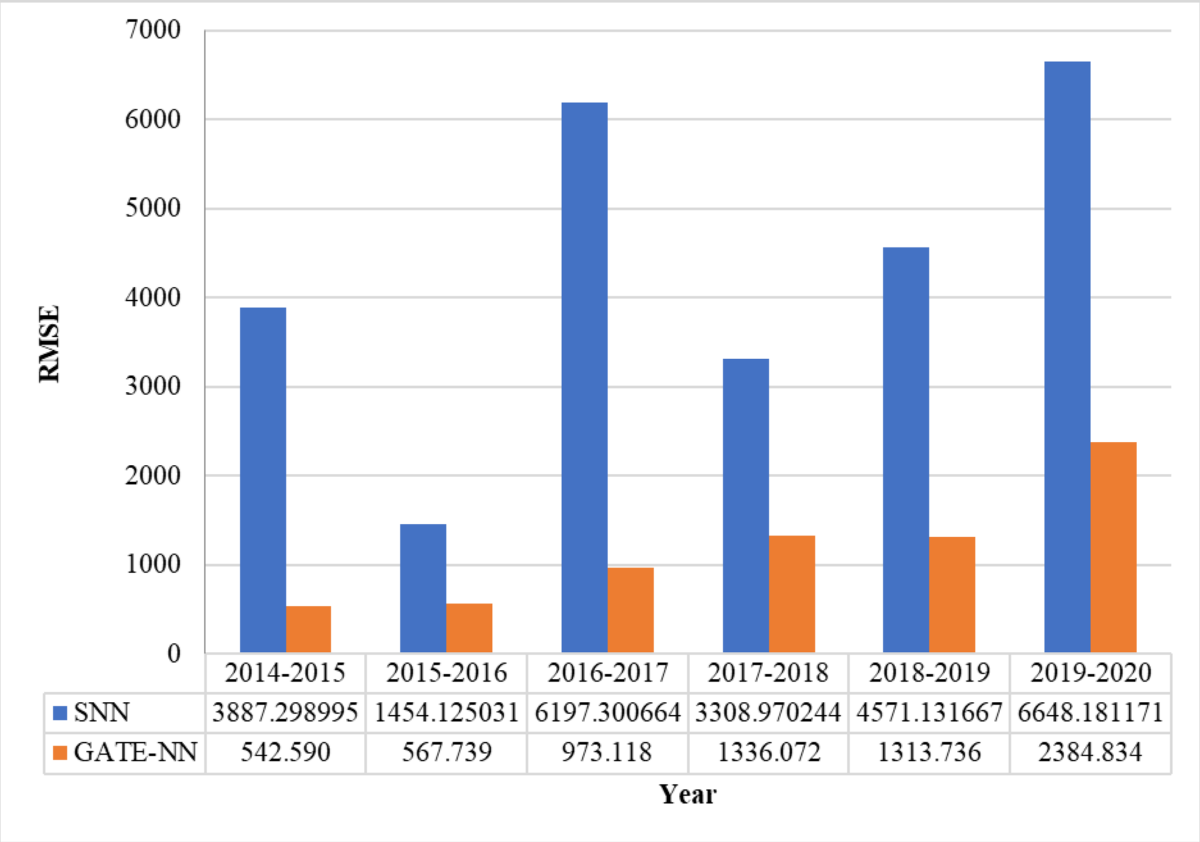

Figure 6.10: Comparison between SNN and GATE-NN in terms of RMSE using three features

It has been observed from table 6.10 and figure 6.10, that the proposed work GATE-NN of crop yield prediction using three feature values performs better as compared to SNN. Here RMSE value of GATE-NN is lesser as compared to SNN model. As the combination of two soft computing approaches; first was TLBO and other was Error Back Propagation Neural Network in GATE-NN has reduced the RMSE value than SNN. TLBO algorithm in proposed work reduces input feature data and hence the increase in prediction accuracy was obtained in comparison to SNN.

6.8.4 Comparison between SNN and GATE-NN in terms of RE using three features

Table 6.11: Comparison between SNN and GATE-NN in terms of RE using three features

S. No.	Year	SNN [1]	GATE-NN
1	2014-2015	22.217	0.319
2	2015-2016	3.195	3.210
3	2016-2017	34.019	6.423
4	2017-2018	20.421	6.355
5	2018-2019	26.934	5.059
6	2019-2020	33.654	14.261

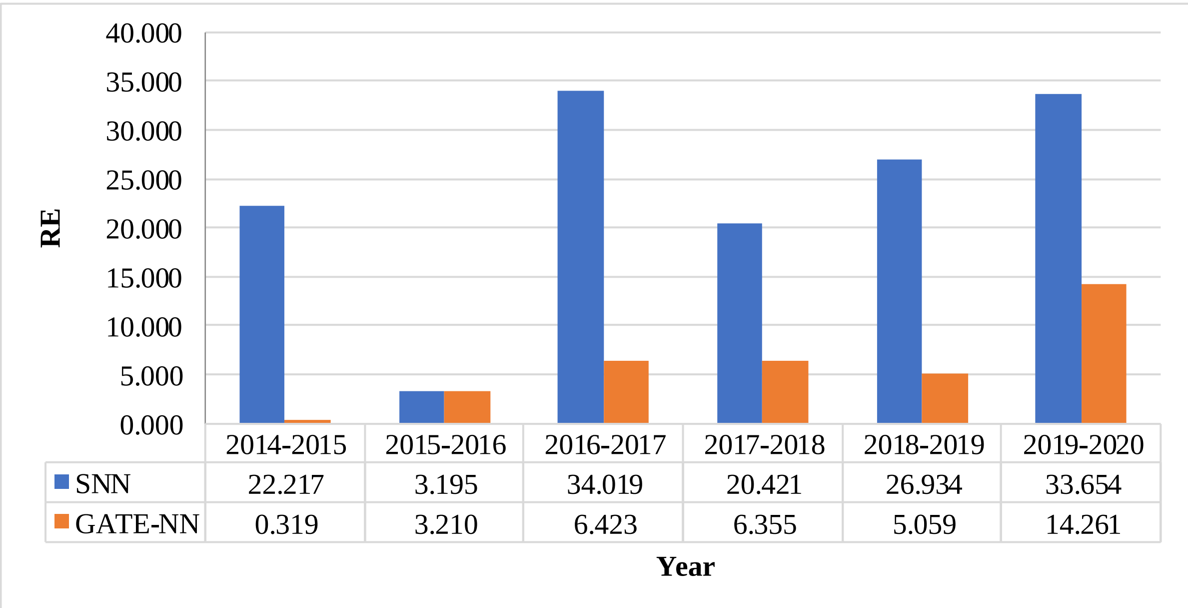

Figure 6.11: Comparison between SNN and GATE-NN in terms of RE using three features

From the table 6.11 and figure 6.11, it is seen, that the relative error of GATE-NN for crop yield prediction work using three feature values is lesser as compared SNN. So, it shows that combination of two soft computing approaches first was combination of TLBO with GA and other was EBP-NN has reduced the Relative Error value in GATE-NN in comparison to SNN.

6.8.5 Comparison between SNN and GATE-NN in terms of Accuracy using three features

Table 6.12: Comparison between SNN and GATE-NN in terms of Accuracy obtained using three features

S. No.	Year	SNN [78]	GATE- NN	Improvement comparison in Percentage from SNN to GATE-NN
1	2014-2015	77.78%	99.68%	21.97%
2	2015-2016	96.8%	96.8%	0.0%
3	2016-2017	65.98%	93.58%	29.49%
4	2017-2018	79.58%	93.65%	15.02
5	2018-2019	73.07%	94.94%	23.04
6	2019-2020	66.35%	85.74%	22.62
	Average	79.9286%	91%	10.6579%

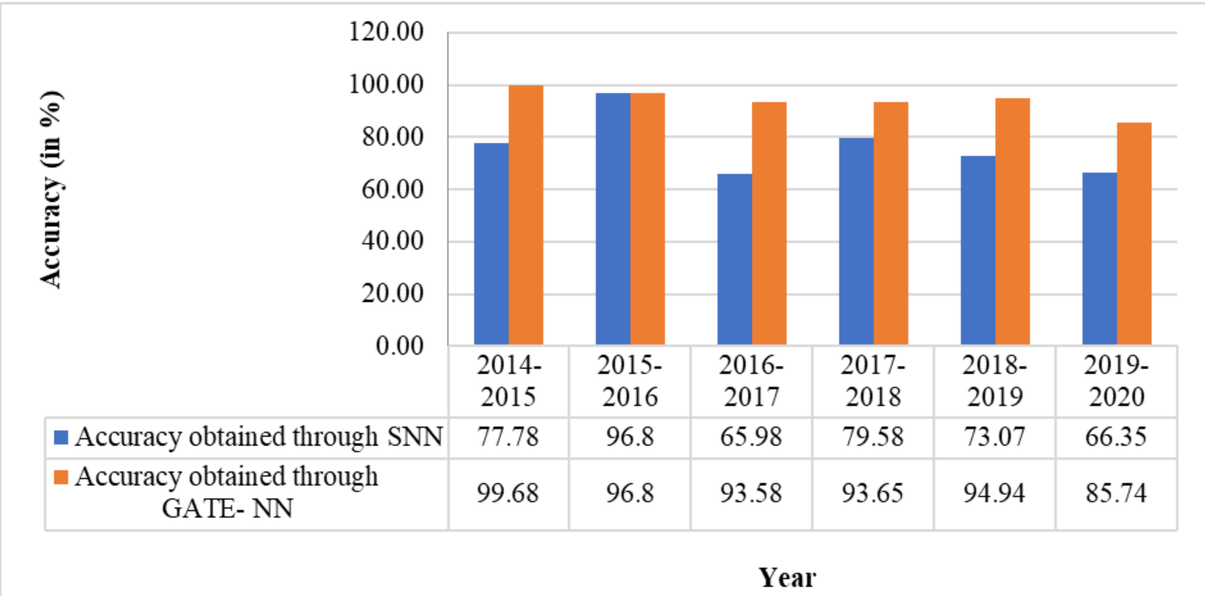

Figure 6.12: Comparison between SNN and GATE-NN in terms of Accuracy using three features

From the table 6.12 and figure 6.12, it is seen, that using three feature values, the prediction accuracy obtained by GATE-NN for crop yield prediction is higher as compared

SNN. So, it is obtained that combination of two soft computing approaches first was TLBO and other was EBP-NN has high accuracy of prediction percentage through GATE-NN in comparison to SNN.

6.8.6 Comparison between SNN and GATE-NN in terms of training time using three features

Table 6.13: Comparison between SNN and GATE-NN in terms of Training Time (in seconds) using three features

S. No.	Year	SNN [1]	GATE-NN	Reduction in time for training from GATE-NN to SNN
1	2014-2015	0.006	0.238	0.232
2	2015-2016	0.0064	0.24	0.2336
3	2016-2017	0.0064	0.068	0.0616
4	2017-2018	0.0063	0.152	0.1457
5	2018-2019	0.0058	0.103	0.0972
6	2019-2020	0.0058	0.187	0.1812
	Average	0.006 secs	0.166 secs	0.160 secs

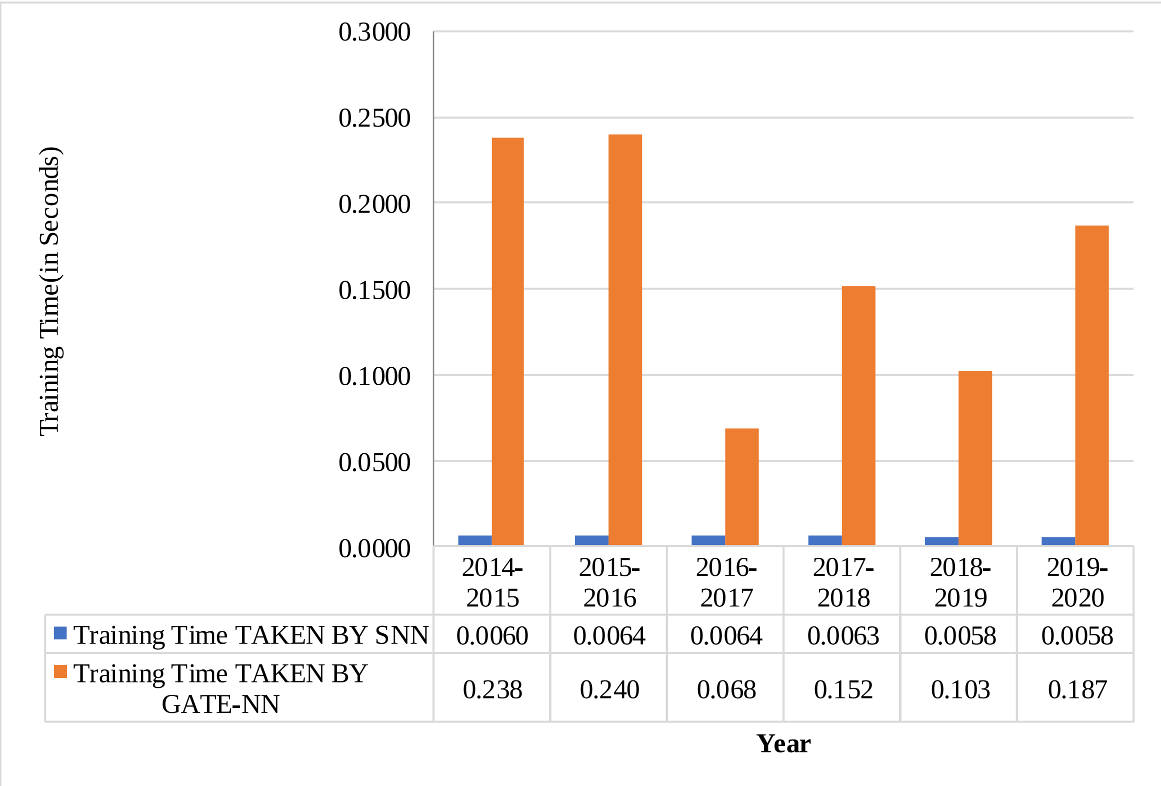

Figure 6.13: Comparison between SNN and GATE-NN in terms of Training Time using three features

It has been observed by table 6.13 and figure 6.13 that by using three feature values, the training time required for GATE-NN was comparatively more than SNN.

6.9 Summary and Discussions

It has been observed from table 6.3 that, GATE-NN developed for the prediction of wheat crop yield using a single feature works well as compared to the previous method SNN. Whereas from table 6.4, it is observed that the RMSE value of GATE-NN is lesser as compared to SNN except for the year 2015-16. Similarly, from table 6.5 it is observed that the RE value of GATE-NN is lesser as compared to SNN except for the years 2019-20. From table 6.7, it is observed that the average training time taken by SNN is almost 0.077 seconds less than GATE-NN. From table 6.6, it is observed that the average improvement in prediction accuracy is almost 4.44% in GATE-NN in comparison to SNN. Hence, by using the one feature vector value: NDVI, the proposed GATE-NN performed better than SNN in terms of prediction of wheat crop yield, RMSE, RE, and prediction accuracy, whereas the execution time taken for training was less in SNN.

It has been observed from table 6.9 that, GATE-NN developed for the prediction of wheat crop yield using three features works well as compared to the SNN. Whereas from table 6.10, it is observed that the RMSE value of GATE-NN is lesser as compared to SNN. Similarly, from table 6.11, it is observed that the RE value of GATE-NN is lesser as compared to SNN. From table 6.13 it is observed that the average training time taken by GATE-NN is almost 0.0.160 seconds more than SNN. From table 6.12, it is observed that the average improvement in prediction accuracy is almost 10.66 % in GATE-NN in comparison to SNN.

Hence, by using the three features value; NDVI, VCI, and SPI, the proposed GATE-NN performed better than SNN in terms of prediction of wheat crop yield, RMSE, RE, accuracy, and the execution time taken for training was less in SNN. Hence, by using the three features value; NDVI, VCI, and SPI, the proposed GATE-NN performed better than SNN in terms of prediction of wheat crop yield, RMSE, RE, accuracy, and the execution time taken for training was less in SNN.

In this chapter, the understanding of SNN for crop yield prediction was done by explaining steps, and diagrams. The work was also tried to make understandable through step-by-step explanation. The results obtained from SNN using NDVI alone and then by using NDVI, VCI, and SPI values were then compared with GATE-NN in terms of various evaluation parameters.

From the results obtained and that are shown in tables and the analytical graphs, it was concluded that the results obtained in SNN using 3 feature values were improved than those found using a single feature. It was also concluded that the proposed GATE-NN has improved results in terms of evaluation parameters, ie: crop yield prediction, RMSE, RE, and Prediction Accuracy whereas the execution time taken for training was less in SNN.

It is summarized; that the proposed GATE-NN developed for the prediction of wheat crop yield production using three features gives better results when compared with SNN broadly except the execution time taken was a bit less in SNN.