Research Article

Predicting Wheat Production in Pakistan by using an Artificial Neural Network Approach

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Abstract | Forecasting of wheat production is of great importance for farmers and agriculture policy makers to improve production planning decisions. Numerous studies proved that traditional econometric techniques face significant challenges in out of sample predictability tests due to model uncertainty and parameter instability. Recent studies introduce several machine learning algorithms to improve time series prediction accuracy. The purpose of this study is to develop a precise wheat production model using artificial neural networks (ANN). A total of 71 years' wheat production data from 1948 to 2018 is divided into training data and test data. The model is trained by using 53 years' data and forecasts the future wheat production for the remaining 14 years. There are 16 indicators used as input variables for wheat production and top ten most important variables highlighted. The findings show, that the model captures much of the trend, and some of the undulations of the original series. The results reveal that the most important features in wheat production includes production prevailing trends, momentum and volatility.

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Introduction

The agriculture sector is one of the most essential components of Pakistan's economy. In year 2016-2017, it contributed 21 percent to the gross domestic product (GDP) and generates 45 percent of productive employment in the country. More than 60 percent livelihood of the rural population depends on the agriculture sector. The agriculture sector plays a key role not only in economic growth, but it is one of the main sectors to reduce poverty, ensure food security and foreign earnings. Within agriculture sector, wheat is the most important grain and a staple food in Pakistan with a contribution of more than 2 percent of the country's GDP. Pakistan is ranked 6th with only 3.5 percent of the world wheat production, with an average of 25 million tons per year (The details are available at: http://www.parc.gov.pk/files/parc_pk/January-15/Status%20Papers/status%20paper%20Wheat%20in%20Pakistan.pdf). With growing population, crop forecasting has become an important research area with several important implications. This study would be helpful for farmers and government to manage storage, transportation, support price and distribution. The findings would be very helpful to design next year import/export strategies. Overall, an accurate forecasting plays a vital role in mitigating food instability and price discovery.

Forecasting is making claims about something that will happen in the future, often based on historical and current data. Forecasting is not a new phenomenon as data analysts are frequently faced with the need to forecast a variable from a set of predictors. There are countless applications of forecasting in our daily life, including weather (Alley et al., 2019; Toth and Buizza, 2019), exchange rate (Rezaee et al., 2018), economic growth (Christensen et al., 2018), energy (He and Lin, 2018), transport (Field, 2018), sales (Sagaert et al., 2018), stock market index (Ren et al., 2018), harvest (Gupta et al., 2018), earthquakes (Ogata et al., 2018), terrorist attacks (Onat and Gul, 2018), heart attacks (Takci, 2018), loan default (Tiwari, 2018) and many more. The main objective of a good forecast is to minimize the forecasting error.

Several studies attempt to forecast crop forecasting particularly with respect to Pakistan (Ahmad et al., 2017; Ali et al., 2015; Masood et al., 2018; Haider et al., 2019). The most common predictors in past studies include rainfall, fertilizer, temperature, tractors and labor. A large number of studies have reported a very strong correlation between fertilizer and wheat production (Azhar et al., 1972, 1974; Mukhtar and Mukhtar, 1988; Saleem, 1989). The study of (Salam, 1981) highlighted that tractorization and labor are also the influency factors. Husnain et al. (2018) documented that endogeneity is a crucial issue in temperature-agriculture nexus.

Most of the researchers forecasted major crops with a variety of econometric models. The most common methods include Exponential Weighted Moving Average (Sabir and Tahir, 2012), Regression Analysis (Karim et al., 2005) and ARIMA model (Muhammad, 1992; Saeed et al., 2000; Badmus et al., 2011; Mehmood and Ahmad, 2013; Iqbal et al., 2005; Arivarasi et al., 2015; Badar et al., 2015; Ali et al., 2015; Zulfiqar and Hussain, 2014). Particularly, ARIMA model approach has remained the focus of massive studies for forecasting purpose. For instance, by using regression analysis, Karim et al. (2005) have forecasted wheat crop production in Bangladesh. Sabir and Tahir (2012) have forecasted wheat crop production with supply-demand projection using Exponential Smoothing model for Pakistan. A large number of studies applied ARIMA model for forecasting. For example, Muhammad (1992) has applied ARIMA model approach to forecast rice production in Pakistan and suggest proper measures to increasing exports. Likewise, Saeed et al. (2000) have forecasted wheat crop area and production employing ARIMA model. In Nigeria, Badmus et al. (2011) used ARIMA model to forecast maize cultivated area and yield. Recently, Mehmood and Ahmad (2013) employed ARIMA model to forecast area of in Pakistan while Arivarasi et al. (2015) applied this model to forecast vegetable trends in India. From a broader perspective, Badar et al. (2015) have used ARIMA model to forecast major food crops including wheat, rice, and maize, area, production and yield in Pakistan. In a similar study, Ali et al. (2015) have forecasted production and yield of cotton and sugarcane using ARIMA model.

In past, as compared to econometric models, application of machine learning in agriculture sector did not get much attention from the researcher. However, in last one decade, artificial neural networks (ANNs) have received great interest in various research fields such as engineering (Ahmadi, 2012; Jani et al., 2017; Shafiei et al., 2014), energy (Olatomiwa et al., 2016), petroleum and gas (Ahmadi and Ebadi, 2014), zoology (Karadas et al., 2017) and agriculture (Moldes et al., 2017; Soltanali et al., 2017; Jiang et al., 2004; Alvarez, 2009; Ghodsi et al., 2012; Haider et al., 2019). For instance, Khoshroo et al. (2018) perform sensitivity analysis of energy inputs in grape production by using ANN model. The authors reported that machinery, diesel fuel and labor had the greatest impact on grape yield. Relatedly, Dahikar and Rode (2014) applied feed forward back propagation ANN by using regional and soil parameters to predict crop yield in India. Very recently, Haider et al. (2019) applied LSTM model to predict wheat production in Pakistan. Artificial neural networks (ANN) have proved to be a more powerful and self-adaptive method as compared to traditional linear and simple nonlinear analyses (Simpson, 1994; Baret et al., 1995). ANN have been widely used for prediction of various complex systems (Naqvi et al., 2018; Haider et al., 2019). This method employs a nonlinear response function that iterates many times in a special network structure in order to learn the complex functional relationship between input and output training data.

In this study, we present Artificial Neural Network (ANN) based approach to forecast wheat production in Pakistan. We also calculate sixteen input indicators as input variables to predict wheat production. Finally, application of feature selection to find out the most important input indicators for wheat production in Pakistan makes this study different from others. The findings of this study would be helpful for farmers (adjust wheat cultivation), governments (wheat storage, food security) and investors (pricing, financial planning according to predicted production).

Materials and Methods

The data and methodology part consist on several steps. A brief detail of all the steps is given below.

Step 01: Data collection

For the purpose of this study annual wheat production data is obtained from Agriculture Marketing Information Service (AMIS). The annual data is collected from 1948 to 2018 (No. of observations = 71). In Table 1, summary statistics of annual wheat production are reported. The average wheat production is 12471 MT with a standard deviation of 7710 MT. It is clear from the (Figure 1), that wheat production in Pakistan has increasing trend with 3301 MT in 1948 to 25500 MT in 2018. The (Figure 2), shows the annual growth rate of wheat production in Pakistan. The average growth rate is only 3.58 percent with a standard deviation of 12.10 percent. The maximum growth of 51.54 percent was recorded in 1954 while the minimum growth rate was -24.63 percent in 1952. The growth rate is shown in Figure 2.

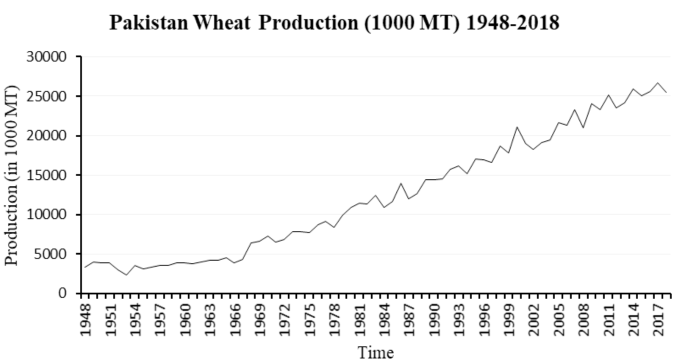

Figure 1: *Annual wheat production growth rate in Pakistan from 1948 to 2018.*

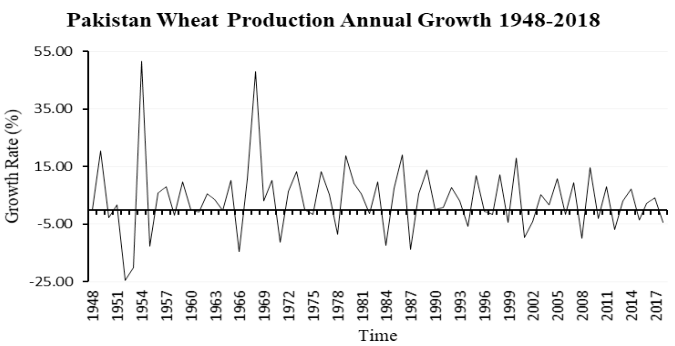

Figure 2: *Annual wheat production growth rate in Pakistan from 1948 to 2018.*

Step 02: Calculate indicator variables-data features

A total of 16 indicator variables are calculated for input, by using the TTR package in R. The details of the indicators are reported in the Table 2.

Table 1: *Summary statistics of annual wheat production and annual growth rate.*

Descriptive statistics	Production (1000 MT)	Growth rate
Mean	12471.11	3.58
Median	11473.00	3.12
Mode	7800.00	0.00
Standard Deviation	7702.09	12.10
Kurtosis	-1.25	4.83
Skewness	0.34	1.25
Range	24307.00	76.17
Minimum	2367.00	-24.63
Maximum	26674.00	51.54
Count	71	71

Table 2: *List of wheat production indicators.*

Identifier	Indicator name
RSI	Relative strength index
MA	Moving average
MACD	Moving average convergence/Divergence
HMA	Hull moving average
APO	Absolute price oscillator
DPO	Detrended price oscillator
MOM	Momentum
MSW	Mesa sine wave
PPO	Percentage price oscillator
BB	Bollinger bands
DEMA	Double exponential moving average
EMA	Exponential moving average
KAMA	Kaufman's Adaptive Moving Average
TRIMA	Triangular moving average
WILDERS	Wilders
ZLEMA	Zero lag exponential moving average

Step 03: Data transformation

In this step, Data type conversions, and scaling and normalization are performed by using Min Max normalization. Below Equation 1 is used for data transformation.

$$y = \frac{(x - \min(x))}{(\max(x) - \min(x))} \quad \text{....} (1)$$

Step 05: Training and testing data

The data is divided into training and test data sets

Links Researchers

by using the 80:20 ratio. The training data (N=53, 1948-2004) refers to the data which is solely used to train the predictive models. The machine learning algorithm picks up the tuples from training dataset and tries to find out patterns and learn from the various observation instances. While the test data (N=14, 2005-2018) is used to get predictions and accuracy of the model. It is important to keep the actual data for the forecast period so that we can assess the precision of our forecast and compare it to the actual realizations.

Step 06: Model training

In this step, we used artificial neural network (ANN) machine learning algorithms and feed the training data features to them and build the predictive model.

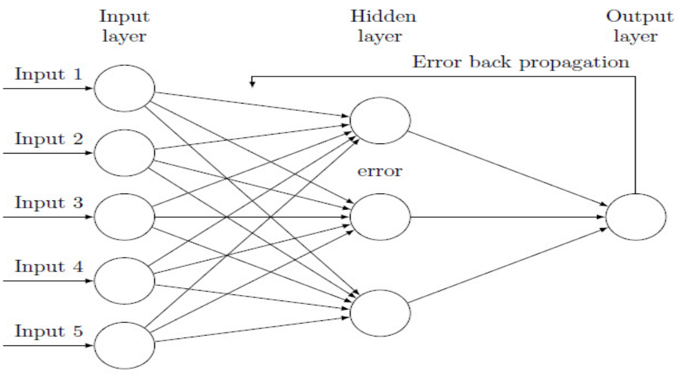

Figure 3: *Neural network architecture.*

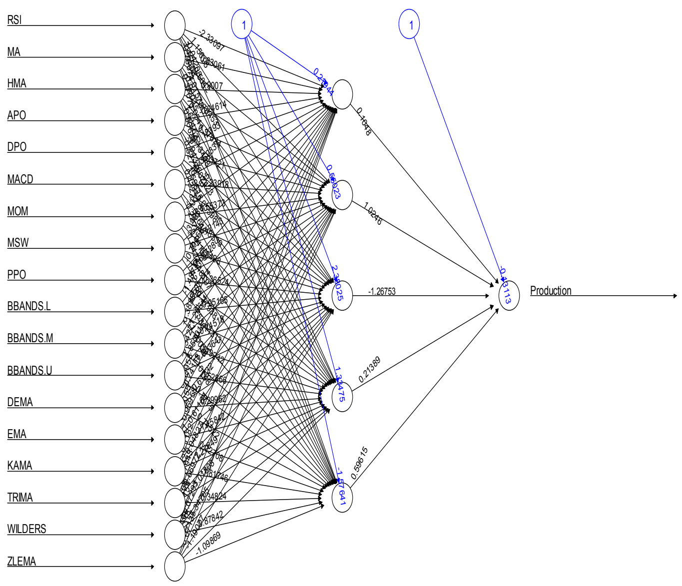

Figure 4: *Neural network architecture (full model).*

Step 07: Predictive model

We have used Neural networks for prediction task. A brief introduction is given below:

Neural Networks: Neural networks are human brain-inspired processors which have ability to learn by training and then store the learned experience for use at later stage when required. They have the ability to derive meaning from complicated data. Neural networks have advantages as compared to the traditional linear models due to their non-linear nature. They have the capability to recognize the non-linear relationship in the input data sample without priori assumption of knowledge of relation between input and output variables. Neural networks have the ability to change its parameters (weights) when dealing with non-stationary and dynamic data. A special function like sigmoid transforms input variables into output variables.

Various models are used for variety of purposes in different fields. Commonly used models include feed forward neural network, back propagation neural network, and multilayer perceptron. Back-propagation is a feed-forward neural network structure which takes the input to the network and multiplies it by the weights on the connections between neurons (also called nodes), sums their product and passes it through a threshold function (normally sigmoid function) to produce an output.

To minimize the error between output and target (actual), error is propagated back into the network. The weights between neurons, on each of the connection are adjusted to the size of the initial error. The input data are fed forward again to produce new output and error. This process continues till the acceptable level of error is achieved. Sigmoid function is the most commonly used transfer function in neural networks and its value ranges from 0 to 1.

For analysis purpose, we used packages of "caret" to run the neural network and package "ROCR" for model evaluation.

Step 08: Model selection

At start we use 16 features. In model selection step, based on maximum accuracy, we select top ten indicators from several iterations of predictive models.

Step 09: Hyperparameter optimization

After feature selection, we try to choose a set of the hyperparameters used by the algorithm in the model such that the performance of the model is optimal with regards to its prediction accuracy.

Results and Discussion

In Model 1 (full model) 18 input variables were used as input variable, while the wheat production was the output variable. The ANN model consists of three layers. The first layer is the input layer, which consists of 18 input variables, the second layer is the hidden layer, with 5 nodes, while the third layer is the output layer, which is the wheat production. The architecture of the model is shown in (Figure 4). The number of layers and hidden nodes are selected by performing hyperparameter optimization. 100 models ere bootstrapped to find out the best combination. The main objective is to minimize the prediction error.

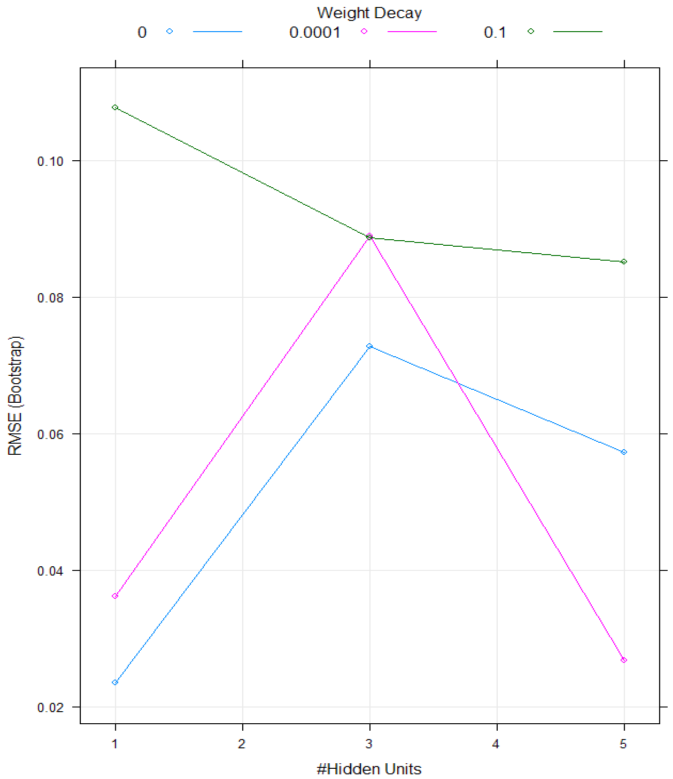

Figure 5: *Hyper parameter optimization for neuron selection (full model).*

The relationship of RMSE with number of neurons and weight decay is reported in the (Figure 5). We can see that the forecasting error is minimum by using 5 nodes and weight decay = .0001. By using the full model, we found mean absolute error (MAE) of 0.05, mean squared error (MSE) of 0.004 and mean absolute percentage error (MAPE) of 5.20.

After running the model one, feature selection is done on the basis of relative importance to predict the wheat production. The results are reported in (Figure 6). The top influencing input indicators include DPO, HMA, PPO, EMA, RSI and so on. However, our results confirm that ZELMA and MSW have very little impact on Wheat Production.

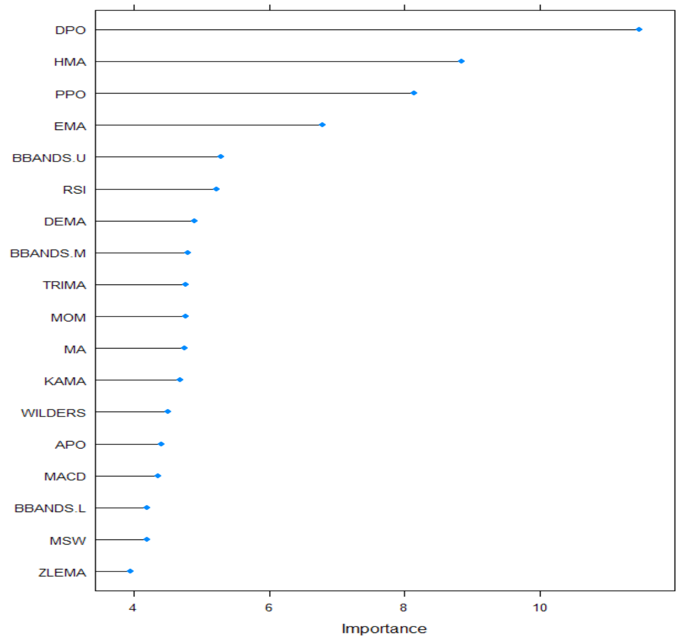

Figure 6: *Relative Importance Plot for Feature Selection.*

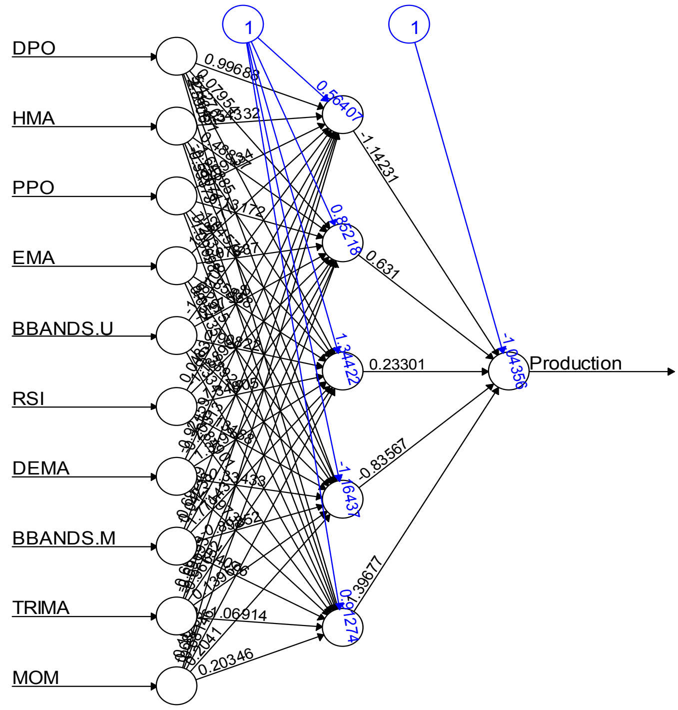

Figure 7: *Neural network architecture (selected features).*

The results reveal that the most important features in wheat production includes production prevailing trends, momentum and volatility, which in turn use to estimate the length of wheat production cycles from peak to peak, or trough to trough, reducing lag, increasing responsiveness by weighting more recent years heavily. The will expand and contract as the price action of an issue becomes volatile or becomes bound into a tight trading pattern.

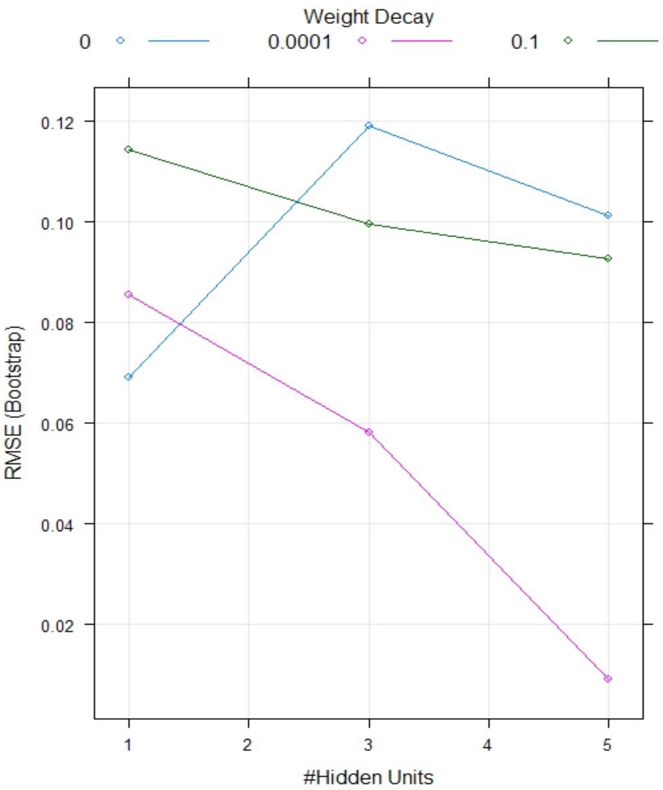

Figure 8: *Hyper parameter optimization for neuron selection (selected features).*

Table 3: *Actual Vs forecasted wheat production 2005-2018.*

Year	Actual production (MT)	Forecast		Absolute value of % error	
		Full model	Selected features	Full model	Selected features
2005	21612	21656	20181	0.20	6.62
2006	21277	22591	20647	6.18	2.96
2007	23295	22908	21226	1.66	8.88
2008	20959	17802	20886	15.06	0.35
2009	24033	24493	21851	1.92	9.08
2010	23311	22675	22231	2.73	4.63
2011	25214	24029	19854	4.70	21.26
2012	23473	20034	22560	14.65	3.89
2013	24211	22490	21969	7.11	9.26
2014	25979	25973	23384	0.02	9.99
2015	25086	23861	21681	4.89	13.58
2016	25633	24537	23018	4.27	10.20
2017	26674	26001	23852	2.52	10.58
2018	25500	23745	22452	6.88	11.95
MAPE [mean absolute percentage error]				5.20	8.80

*Test data was 0.2*71=14 years (2005-2018).*

In model II, top ten importance variables ere used as input variables while wheat production is the output variable. The architecture of ANN model with selected features is shown in (Figure 7). The model is optimized by using hyperparameter optimization. After bootstrapping 100 different models, it is clear in (Figure 8), that weight decay of .0001 with 5 neurons is the optimal ANN architecture. In model II, 8 input variables are removed but the accuracy decline is very small because of their least importance in forecasting. In Model II, we found a slight increase in the forecasting error. The results show that MAPE increased to 8.80 from 5.20.

The test data was 20 percent of the total data. So, we have 14 years (2005-2018) to validate our ANN model. In Table 3, we report the actual wheat production (MT) and forecasted production using full model and model with selected features. The (Figure 9) shows the movement of actual and predicted wheat production from 2005 to 2018. The absolute value of the % error is reported from 2005 to 2018. It is evident from the (Figure 9) that ANN model captures much of the trend, and some of the undulations of the original series. Overall, the model performs very well. We can observe the same patterns between actual and predicted values with very small differences.

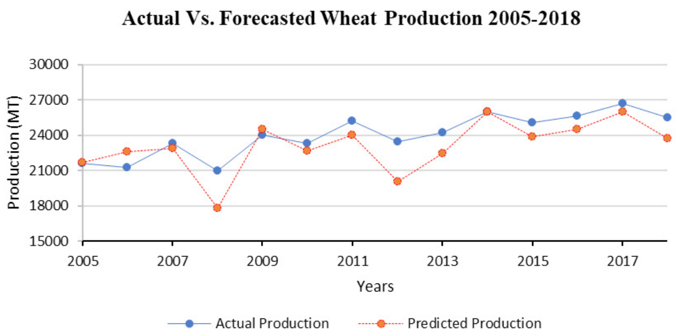

Figure 9: *Actual vs predicted wheat production from 2005 to 2018.*

These results can be compared with relevant studies in different countries. For instance, Safa et al. (2015) used ANN model to predict wheat production in New Zealand. According to this study the most influential factors in New Zealand includes farm conditions, machinery conditions, and farm inputs. However, this study is limited to wheat fields in Canterbury only. Our study is in line with Haider et al. (2019). The authors applied LSTM neural network to predict wheat production in Pakistan and reported that neural networks perdition can be used as guidelines for wheat prediction. In comparison, our study used 78 years of data with 16 indicators to find out the best inputs for wheat prediction. Relatedly, Dahikar and Rode (2014) applied feed forward back propagation ANN by using PH, temperature, rainfall, depth and nitrogen predict crop yield in India. The authors suggest that ANN model is beneficial tool for crop prediction. However, this study mainly focused on the best ANN model and software selection. The authors recommend Matlab for efficient analysis. Finally, the study of Gandhi et al. (2016) used neural networks explore the factors affecting the rice production for various districts of Maharashtra state in India. By using 5 years data of 27 districts, the authors documented that by using ANN models, an accuracy of accuracy of above 95 percent can be achieved.

Conclusions and Recommendations

Focus of this study was forecast of wheat production in Pakistan. Artificial Neural Network (ANN) model was employed by using the annual wheat production from 1948 to 2018. The data was divided into training data (80 percent) and test data (20 percent). The model was optimized by using hyperparameter tuning. In model I, the wheat production was the output while 18 indicators were used as input variables. Feature selection was done to find out the most important input variables in wheat production. The top influencing input indicators include DPO, HMA, PPO, EMA, RSI. In other words, production trends, momentum and volatility which estimate production cycle, lags reduction and increase in responsiveness are the important features in wheat production. In model II, top ten relatively important indicators were used as input variables. The findings show a slight decline in the prediction accuracy in model II. The findings suggest that feature selection is an important consideration while predicting wheat production. This study may have important implications for policy makes, farmers and investors. For instance, the government can design adequate policies regarding wheat cultivation, storage, food security and pricing. Likewise, the farmers can adjust the wheat cultivation to avoid heavy losses due to wheat surplus. Furthermore, consideration of the most important wheat production indicators can be helpful for decision making.

Novelty Statement

We presented Artificial Neural Network (ANN) based approach to forecast wheat production in Pakistan. We also calculated sixteen input indicators and finally, application of feature selection to find out the most important input indicators for wheat production in Pakistan makes this study different from others.

Author's Contribution

Faheem Aslam developed the theoretical formalism, data collection, performed the data analytics and R coding. Aneel Salman wrote the manuscript. Inayatullah Jan contributed to preparation of final version of the manuscript and supervised the project. All authors provided critical feedback and helped shape the research, analysis and manuscript.

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