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Original Article

Exploring Groundnut Area, Production and Yield Trends using Deep Learning

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Abstract - *Growing groundnuts is an important part of Andhra Pradesh (AP) agricultural economy. It brings a lot of revenue for the regions and transforms the lives of those living in rural areas. To make smart decisions about how to run a farm and use resources wisely, it is important to look at trends in the area, production, and the yield of groundnuts over time. Conventional statistical techniques frequently fail to represent intricate temporal patterns accurately, underscoring the necessity for more resilient, data-driven methodologies to improve decision-making and promote the enduring viability of groundnut agriculture. This paper suggests a new way to use a deep learning method called an Autoencoder (AE) - Long Short-Term Memory (LSTM), named AELSTM, to look at the patterns in the state of AP expanding groundnut area, production, and yield. The main goal of the suggested strategy was to get clear information that would help people make decisions and create policies based on data that would help to protect and grow groundnut farming in the country. Indiastat, a statistical database, collected secondary data on groundnut area, production, and yield in AP from 1990 to 2023. AELSTM was used to do trend analysis. Initially, AE was utilized for dimensionality reduction, resulting in a compressed lower-dimensional latent representation. These small representations were transferred to an LSTM network to model temporal relationships, and trend analysis was done to find long-term patterns in the data. We used R^2 values to check the accuracy and quality of the trend representation by comparing the proposed method to traditional statistical trend models and architectural base models. The proposed model R^2 values 0.95, 0.96, and 0.94 for area, production, and yield, respectively, show that it works better than traditional statistical models and architectural base models like the dense autoencoder, vanilla-LSTM, and Sequence-to-Sequence (Seq2Seq).*

Keywords - *Area Production and Yield, Autoencoder, Groundnut, Trend, Kalman Filter, Long Short-Term Memory.*

1. Introduction

Groundnut is a vital oilseed crop around the world. The "king" regarding oilseeds is known around the world as a peanut or monkey nut. This plant comes from Brazil and grows in tropical, subtropical, and moderately warm climates all over the world [1]. [2] Groundnut (Arachis hypogaea, Li) is a very important Kharif oilseed crop that helps the Indian agricultural economy a lot. [3] The acronym for "groundnut" originates from two Greek words: "arachis," which means "legumes," and "hypogaea," which means "underground pods". [4] Groundnuts are native to parts of Brazil, Peru, Argentina, and Ghana. They made their way to India in the first half of the 16th century. [5] People who like legumes or "beans" love groundnuts because they are crunchy, sweet, and have a deep, nutty flavour. [6] They provide an adequate supply of calcium, phosphorus, vitamin E, zinc, iron, and B vitamins. They are also known for their high protein content (26%) and long shelf life. [7] Groundnuts have an abundance of nutrients that may help fight cancer, like folic acid, phytosterols, phytic acid, and resveratrol. [8] Groundnut seeds may possess a level of oil of 44–50%, depending on the type and the conditions in which they are grown. [9] Groundnut oil serves the purpose for manufacturing soap and cosmetics as well as cooking. [10] Residual oilcake is a good fertilizer because it has 7 to 8% nitrogen (N), 1.5% phosphorus ($P2O5$), and 1.2% potassium ($K2O$). India remains the second-largest supplier of groundnuts in the world, following China. [11] India grew almost 16% of all groundnuts globally in 2016. [12] Tamil Nadu (TN) (1 million tons (Mt)), AP (1 Mt), and Gujarat regions (2.5 Mt) in India that grow the most groundnut. Together, they have about 4.56 million hectares of land under cultivation. [13] The total production from 2015 to 2016 was 6.77 Mt, with a median yield of about 1486 kg per ha. [14] But for several instances, the area used to grow groundnuts has been getting smaller lately. [15] Planners are worried about the declining area of groundnuts being grown in India because they are such an important crop for edible oilseeds. [16] India is one of the leading producers of groundnuts globally. In 2005, India became the second-biggest supplier of groundnuts globally, with 5.9 million tons of groundnut seeds and 1.5 million tons of groundnut oil made each year. Furthermore, India has the most land used for growing groundnuts. Most of India's production and area are in the states mentioned above. Groundnut constitutes about 25% of all the oilseeds grown throughout India at present.

But this share has been steadily going down because India became autonomous, when it accounted for about 70% around 1950. There are many kinds of Indian groundnuts, such as Red Natal, Spanish, and Bold. Individuals taste sweet, possess an elegant nutty taste, and are frangible. They also last longer than most other foods. Some areas that grow crops have soil conditions that are perfect for moist, flawless, and groundnuts in their shells. Groundnuts remain accessible annually because they are harvested twice a year, during March and October. Groundnuts serve as a significant ingredient for protein across India, and they tend to thrive in areas that get rain. It originates in many places between 40°N and 40°S latitude. People eat the nuts in different ways, or they crush them to make vegetable oil for people to eat and protein-rich food for animals. There are many other names for groundnut in the area, viz, pig nuts, peanuts, pygmy nuts, monkey nuts, goober peas, and earthnuts. A peanut is not a nut, even though it looks and sounds like one. It is a legume. The rest of the manuscript is hereby: Section 2 describes the literature survey, Section 3 provides the methodology, Section 4 addresses the results and discussion, and Section 5 demonstrates the conclusion.

2. Literature Survey

Numerous explorations seemed fulfilled by deploying analysis patterns with agricultural crops. A limited number of them were evaluated here. [17] In the past, a study looked at the present situation regarding groundnut area, production, and yield across India. Present research was implemented employing secondary information obtained from multiple reports in the Directorate of Economics and Statistics. This research showed that considering the overall worth of groundnut, besides area, production, and yield, is increasing. The area has demonstrated an adverse pattern with a compound annual growth rate (CAGR), while production and yield are showing a positive trend of 1% and 3.26%, respectively. This indicates that the production has a bigger effect on the yield than the area. CAGR of area, production, and yield regarding groundnut in India, the vital growing states show a poor trend for all states except Rajasthan and Madhya Pradesh. [18] This research indicated that farming of cereals, pulses, and economic crops has led to a decline in area and production of minor millets. Indiastat.com has secondary information on area, production, and productivity with lesser coarse grains from 1990-1991 to 2019-2020. Information was examined adopting descriptive statistics as well as linear growth rates. [19] Statistical Package for the Social Sciences (SPSS) is a tool for gathering as well as analyzing data. The average area, production, and productivity of groundnuts were 352.12 thousand hectares, 513.40 thousand MT, and 1351 kg/ha, respectively. CAGR of groundnut area, production, and productivity was determined likely substantial with beneficial ($R = 0.652^{**}$, 0.940^{**}, and 0.603^{**}) with a rising direction with CAGRs of 3.2, 6.4, and 2.8 percent. [20] Calculated the yield based on groundnut within multiple smallholder agricultural systems in northern Malawi, and noticed that the yield, including Vegetation Indices (VIs), was obtained over multitemporal PlanetScope satellite data. For the prediction, we used Multiple Linear Regression (MLR). [21]

This study detected patterns in the amount of groundnut land, production, and productivity in different parts of Chhattisgarh. The area dedicated to groundnut cultivation is increasing significantly due to improved irrigation infrastructure and farmers' willingness to adopt low-cost input technology for their crops ($R=0.70^{**}$). The number of groundnuts produced is going up in all of Chhattisgarh's districts ($R = 0.73$), resulting in a favorable and important trend. The productivity pattern based on groundnut seems to be greatly expanding in most districts ($R = 0.68^{**}$) because farmers are using more fertilizers and pesticides, and the introduction of High-Yielding Varieties (HYVs).

This study utilized time series data from New AP for the period 2003-2018. This investigation aims to determine the optimal ARIMA approach for predicting and modeling the area, production, and yield of groundnuts in the latest AP. [22] CAGR was used to track the area, production, and yield of groundnuts from 1970–71 to 2018–19. The investigation suggested the area grew faster in Periods I and II. The Technology Mission on Oilseeds (TMO) and All India Coordinated Research Project (AICRP) on oilseeds have contributed to this rise. These projects focused on transferring technology, creating High-Yielding Varieties (HYVs), and providing timely input support. [23]

This research aims to define structural mutation points and examine long-term trends in India's groundnut trade from 2005 to 2024, utilizing historical data on trading quantity and value obtained from Trade Map. We used Standard Normal Homogeneity (SNH), Buishand's range, and Pettitt's tests to identify mutation points. We used Sen's slope assessment to determine the significance as well as the size of trends. [24] This research used CAGR, the instability index, and the decomposition analysis to do the area, production, and yield remaining -0.14%, 1.05%, and 1.2%, respectively. Groundnut yield and production are going up, as well as the area, which has shifted over time. The classification of area, production, and yield, as well as collaboration, affects the yield impact, which was the main reason why groundnut production went up; subsequently, the relationship impact with area influence. [25] This study used an exponential function to figure out growth rates, the coefficient of variation, and Cuddy Della Valle's index, which determines the instability. Applying the Minhas decomposition approach, figured out how much area with yield each contributed to the modifications to the outcome. The research utilized secondary information spanning 2 decades, specifically, divided over two stages: Stage I (1996 to 2006) and Stage II (2006-2016). [26] This investigation used secondary data from the years 2002–03 to 2019–20. To find out the growth rate with fluctuation. Except for Rajasthan (7.667%), the area for growing groundnuts shrank, and the number of groundnuts grown in TN, Karnataka, and AP also fell. Gujarat possessed an unprecedented expansion rate for production of 4.442%. The uncertainty index revealed that groundnut production was more unstable in Gujarat, 41.660% as well as AP, 44.453%. [27]

This study used the Just plus Pope production method to look at how climate change factors like rainfall and high and low temperatures affect the average groundnut yields as well as their inconsistency over Kharif plus Rabi seasons all over various agro-climatic regions. The findings from the years 2005 to 2019 showed that rainfall and the lowest temperature are favourable for yields and negative for risks, while the highest temperature is undesirable for yields and favourable for hazards throughout the Kharif season. [28] This study assessed the variations and fluctuations in the area, revealing a decline in productivity and production throughout the period from 1995 to 2011. CAGR of groundnut area, production, and productivity through this time span exhibits an adverse inconsistency. The investigation demonstrates how much the production of groundnuts can change. The moderate instability and variability in the AP groundnut crop were caused by the fact that both area and productivity moved in accordance. [29]

This investigation evaluates the effects of climate variation indicators, including weather and rainfall, on CO_2 emissions, regarding farming results in India, adopting the crop production index as a metric, and considering an analysis of the region from 1990 to 2022. We can see long-term trends thanks to the 33-year analysis. The Autoregressive Distributed Lag (ARDL) approach will show how climate variables affect agricultural productivity for each of the small and rangy terms. People are starting to see climate change as a problem that affects the whole world, and agriculture constitutes one of the areas that will be influenced most adversely. [30] Climate modification is a big Potential risk for farming and food security, and unpredictable weather has made crops less productive all over the world. According to forecasting, the mean temperature around the world is going to increase by 2.0 to 6.4°C, with sea level rise by 59 cm in the 21st century. Weather elevation that has never happened before has caused more thunderstorms, extreme heat, and dryness, plus strange patterns. Modifications in the climate may exert major impacts on weeds, diseases, insects, and pests in numerous forms. For example, climate change can cause weeds, diseases, insects, and pests to spread to more areas, reproduce more frequently, and survive the winter more effectively. [31] This research examines the consequences of temperature rise for the yield of principal crop varieties across Perambur district, TN, over a span of 5 successive years (2015 to 2020). This district receives most of its water from rain. It is an important supplier of maize and cotton, and farming is the main way that people make a living there. Climate factors like temperature, rainfall, and seasonal changes have a big effect on how productive farms are. The research utilizes statistical techniques, including trend assessment, regression, and correlation, to evaluate the association between weather factors and yield. This research indicates the district's yearly rainfall ranged from 529.44 to 1004.73 mm, with a mean of 766 mm. It also shows that the highest and lowest temperatures have been declining over decades. [32]

This study employed an ex-post facto design to examine the socio-economic variables that influence groundnut production in Kenya. We got information about the characteristics of 323 farmers who grew groundnuts during the main cropping season of 2014 using purposive, multistage, and simple random sampling methods. We used multiple regression analysis to look at how autonomous factors affect relying factors to test hypotheses. [33]

This study aimed to evaluate socio-economic aspects of groundnut landowners, ascertain the financial viability of production, assess the value utilization beneficial, and identify challenges faced in groundnut cultivation. We randomly picked 99 cultivators who grow groundnuts from the different farms in the municipality's area. A gross margin and cost-benefit analysis were done to see how profitable it is to grow groundnuts. [34] This study revealed that the dominant residence heads were adults (52–54years), family (95–100%), uneducated (84%), and predominantly male (95–100%). Socio-economic status influences not only the selection of cowpea varieties but also the production, management, and storage of cowpeas. India grows groundnuts, but the amount of land set aside for them has shrunk over the past ten years. Because of this drop, farmers and policymakers are becoming more worried about the future of groundnut farming in the country and how long it will last.

Many studies have used linear and polynomial regression and other standard statistical methods to look at trends in farming. However, these methods do not work well for long-term agricultural data because they do not show the complicated, nonlinear, and irregular patterns and relationships that change over time. In recent years, deep learning has advanced significantly, suggesting it could be a valuable tool for time series analysis, particularly in identifying subtle patterns and changes in data organization. While studies employing effective hybrid deep learning techniques for assessing multivariate agricultural data exhibit limitations, especially concerning groundnut trends in India, these approaches retain significant potential. Most research has concentrated solely on prediction or classification studies, neglecting the comprehensive applications of temporal pattern recognition for trend analysis. The present analysis fills in the gaps in previous research by suggesting a new way to explore long-term trends within groundnut area, production, and yield for AP. It accomplishes these goals by combining an autoencoder and an LSTM model. The research seeks to demonstrate the efficacy of hybrid architectures in agricultural time series trend analysis by contrasting the proposed method with traditional statistical models and standalone deep learning aspects.

The following points are presented concerning the gaps in research that were identified in the literature review.

- Absence of a modern survey in the trend analysis of area, production, and yield utilizing advanced machine learning methodologies.
- Yield factors are only partially integrated beyond trend analysis.
- The insufficient comparison between traditional statistical models and advanced machine learning methodologies is a concern.
- There is inadequate use of trend forecasting utilizing deep learning methodologies.

The innovative aspect of this research is the proposed AELSTM approach, which combines an autoencoder with long short-term memory algorithms to investigate long-term trends in area, production, and yield of groundnuts in AP. The proposed hybrid model employs an autoencoder for dimensionality reduction and long short-term memory to simulate temporal interactions. Most statistical approaches have difficulties with complex nonlinear trends and temporal dependencies. This new technique not only makes trend analysis more accurate, but it also allows us a more reliable and scalable way to look at agricultural trends in a multivariate time series. This is a tremendous improvement in this investigation.

2.1. Contributions

This study's primary findings are listed below:

- An innovative hybrid deep learning method called AELSTM was proposed. It uses the best parts of autoencoders to reduce the number of dimensions and long short-term memory to determine temporal relationships in agricultural time series data.
- The proposed method is more accurate than standard statistical methods and individual deep learning models when it comes to finding long-term trends in groundnut areas, production, and yield in AP.
- Multivariate agricultural data, encompassing things like area, production, and yield, is often used to give a whole picture of groundnut trends.
- The investigation offers practical information that assists policymakers and agricultural officials in making intelligent choices to maintain and improve groundnut cultivation.

3. Methodology

This research proposed an AELSTM to investigate the area, production, and yield trends of AP. The suggested method is employed to obtain precise information that makes decisions based on data and makes policies to keep and improve groundnut farming in the country. Indiastat provided the input data, which included the area, production, and yield for groundnuts in AP. The Kalman Filter (KF) was adopted to process the data so that missing values could be handled quickly and easily, and normalization could be done. After preprocessing, AELSTM was used to perform trend analysis. Figure 1 shows an outline layout of the suggested AELSTM. Following is a full description of each process.

3.1. Trends in Groundnut Cultivation of AP

Groundnut is a prominent rainfed crop in AP that helps many small and marginal farmers earn incomes. A number of factors that are all connected have affected groundnut farming trends in the last 20 years. The manufacturing process has been greatly affected by climate change, especially the unpredictability of monsoon rains and the frequency of droughts. Poor monsoon years often have less area for planting and less production, while good monsoon years have more output. However, problems with irrigation infrastructure still make it hard for groundnut farming to grow beyond areas that get rain. Farmers also need to reflect on the state of the market, such as how the price and popularity of groundnut oil and kernels are changing, when they determine how to divide up their land. Over time, government policies and efforts to aid rainfed agriculture have altered. This has changed how crops are cultivated and how easy it is to get inputs. The soil in certain locations has gotten worse, which makes it much harder to grow crops.

These things have caused clear trends, with times when the area and production grow slowly, followed by big changes caused by the weather and the economy. These patterns are hard to explain and are always changing, so it is important to know about them. The suggested AELSTM approach uses this information to track both gradual long-term changes and sudden changes in the area, production, and yield. This presents practical information for developing policies and managing crops in AP rainfed agriculture.

3.2. Data Acquisition

Indiastat is an online database that has accurate and current socio-economic and statistical data, where the input data was collected [35]. It is a useful tool for researchers, policymakers, and analysts because it enables them to access a lot of data from different areas, like farming, education, health, economics, ecology, and facilities. Indiastat provides comprehensive time series information regarding crop area, production, and yield-associated factors for agricultural studies at national, state, and district levels. The input data gathered comprised area, production, and yield. The collected information covers an era of 33 years, from 1990 to 2022.

Table 1 shows how the area, production, and yield of groundnuts have changed over the past 33 years. The area used for growing groundnuts has been steadily decreasing, going from about 2400 ha to fewer than 700 ha, as shown in Figure 2. The decrease suggests that people are less interested in growing groundnuts.

Figure 3 shows a rapid drop in groundnut production, with values going up and down but overall decreasing from 2500 tonnes to fewer than 500 tonnes. This decline is because the area is getting smaller and the yield is not stable. Figure 4 shows the trend in groundnut yields. This trend is more unstable, with no apparent increasing or decreasing direction. This suggests that yields are not stable, even with technological or agronomic changes.

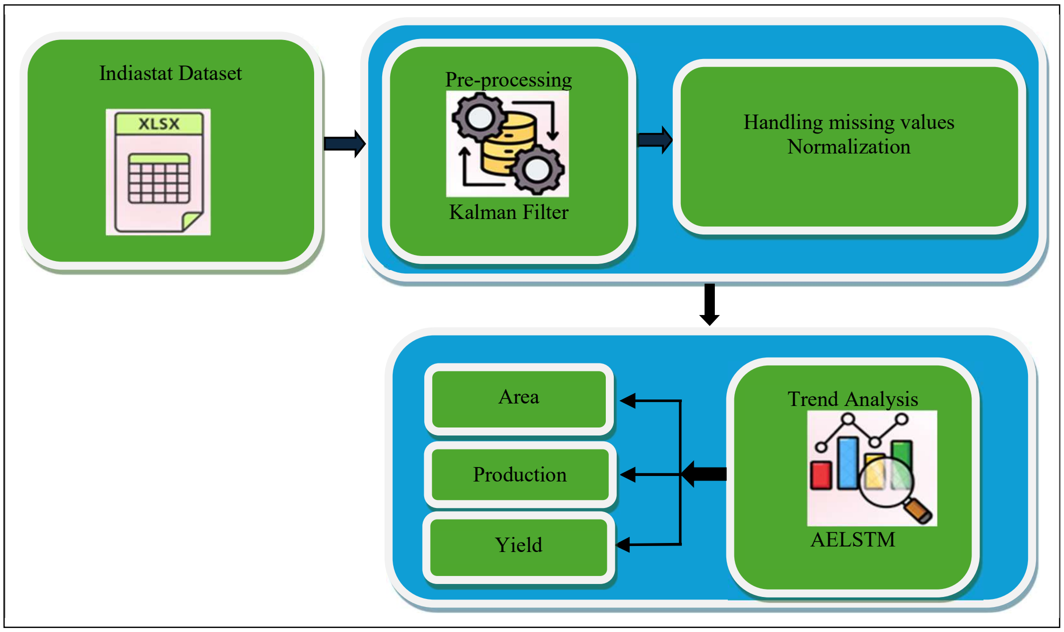

Fig. 1 Block diagram of the proposed AELSTM model

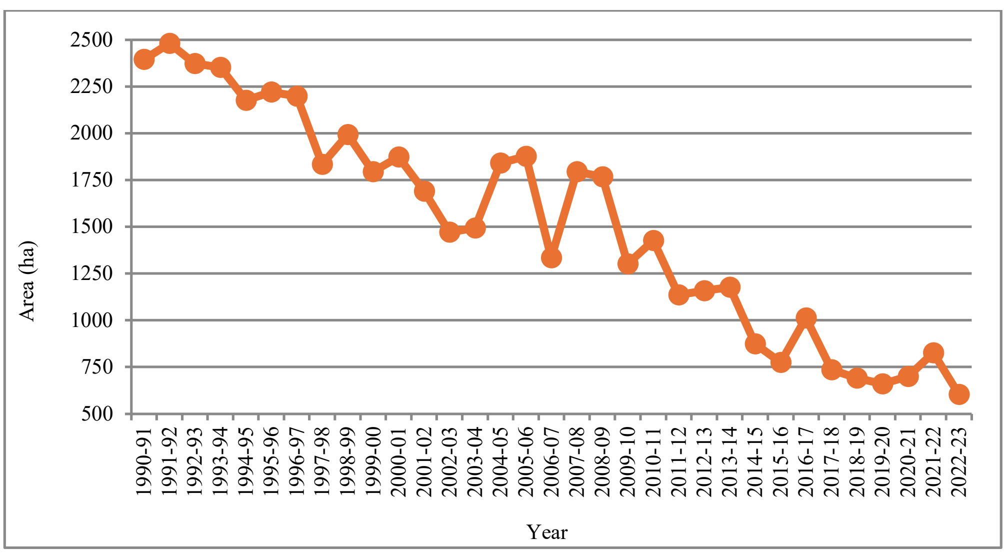

Fig. 2 Analysis of the groundnut area from 1990 to 2023

Table 1. Block diagram of the proposed AELSTM model

Year	Area (ha)	Production (tonnes)	Yield (kg/ha)
1990-91	2394	2267	947
1991-92	2481	2152	867
1992-93	2372	1965	828

1993-94	2352	2546	1082
1994-95	2176	1671	767
1995-96	2220	2625	1183
1996-97	2198	2045	930
1997-98	1834	1156	630
1998-99	1992	2155	1082
1999-00	1795	1089	607
2000-01	1873	2142	1144
2001-02	1690	1249	739
2002-03	1470	820	558
2003-04	1493	986	660
2004-05	1841	1639	890
2005-06	1876	1366	728
2006-07	1334	743	557
2007-08	1795	2604	2615
2008-09	1766	1554	880
2009-10	1301	1006	2128
2010-11	1426	1107	776
2011-12	1136	582	513
2012-13	1158	780	674
2013-14	1176	881	749
2014-15	874	493	564
2015-16	775	801	103
2016-17	1013	603	595
2017-18	735	550	748
2018-19	690	530	768
2019-20	660	510	773
2020-21	700	540	771
2021-22	825	515	625
2022-23	604	487	806
Total	49,359.2	37,496.3	22,867
Mean	1,452.33	1,136.25	693.24
Standard Deviation	598.13	647.21	407.68

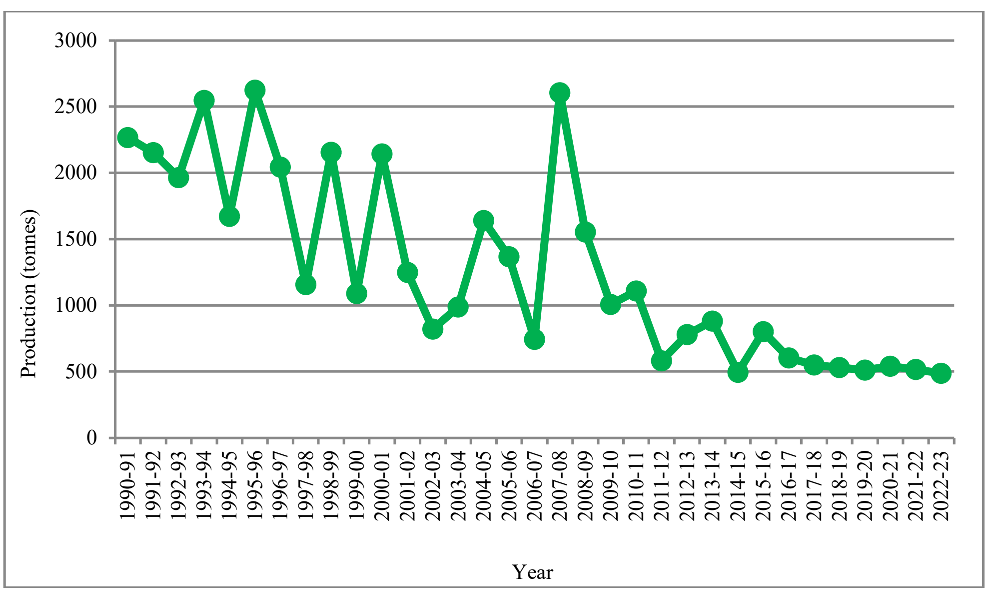

Fig. 3 Analysis of groundnut production from 1990 to 2023

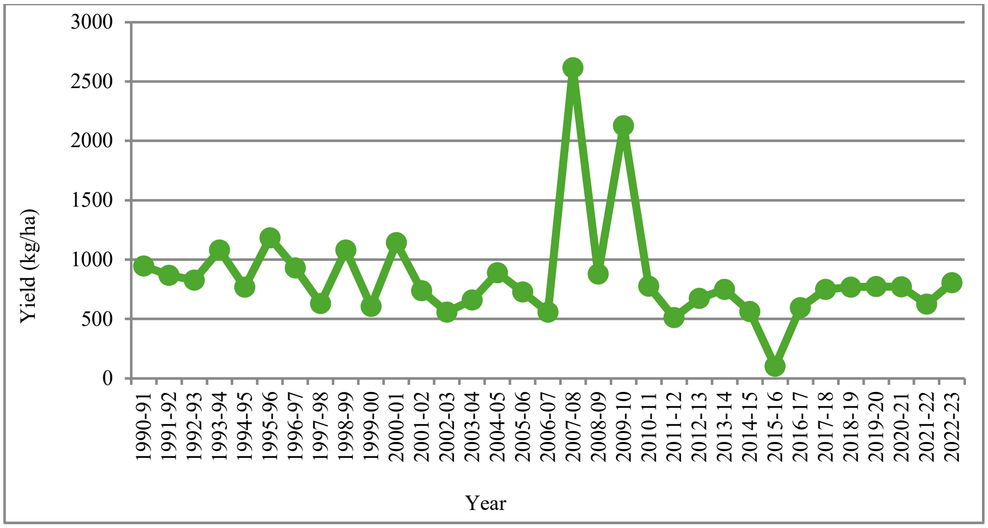

Fig. 4 Analysis of the groundnut yield from 1991 to 20223

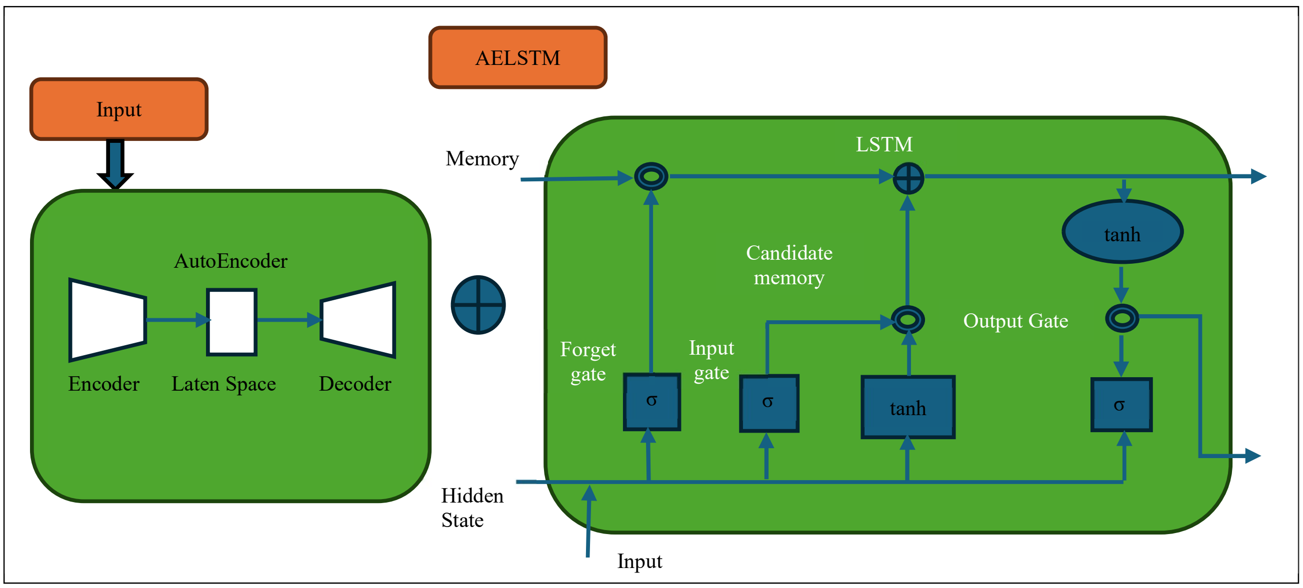

Fig. 5 Architecture of AELSTM

3.3. Preprocessing via KF

KF is employed for preparing data for long-term agricultural time series. It handles missing values and normalizes input data more easily. KF uses a recursive prediction-update technique to combine previous state estimations with observed data to figure out incorrect or ambiguous values. It additionally makes it possible to keep improving state estimates without needing a full data history, allowing it to work with enormous datasets. The filter uses the system's dynamic model to guess what the future state will be and how sure it is, which works even though measurements are unreliable [36]. The current update modifications are estimated based on fresh data, making sure they are still accurate even when data is missing, as seen in Equation 1.

$$\hat{y}_{k+1|k} = B\hat{y}_{k|k} + Cu_k + TS^{-1}(x_k - D\hat{y}_{k|k} - Eu_k) \quad (1)$$

Here, $\hat{y}_{k+1|k}$ indicates state estimates $\hat{y}_{k|k}$, denotes the updated state estimates, B, C, D, and E state transition, monitoring, input, and feed-through matrices, and u_k represents the measurement noise accordingly. KF uses the prior forecast and system behaviour to anticipate the subsequent state and associated uncertainty. This works without any additional information by forecasting assumptions in the future, shown in Equation 2.

$$P_{k+1|k} = (B - SR^{-1}D)P_{k|k}(B - SR^{-1}) + Q - SR^{-1}S \quad (2)$$

Here, $P_{k+1|k}$ is the prediction error covariance and $P_{k|k}$ represents posterior state estimate covariance. The triplet values of Q, R, and S constitute a collection of basic random variables affecting the statistical analysis method. KF resets the state forecast by changing it based on the new information and improving the error covariance. This makes sure that the filter is strong even when data is missing, as shown in Equation 3.

$$L_k = \left(BP_{k|k-1}D^T + S\right)\left(DP_{k|k-1}D^T + R\right)^{-1} \quad (3)$$

Here, L_k is the pre-processed output, and the output data are normalized to ensure that the feature scales are the same before being sent to the autoencoder long short-term memory. Lastly, the KF works well with missing values and does a better job of normalizing the incoming data.

3.4. Trend Analysis via the Proposed AELSTM Model

AELSTM shows the trends in AP groundnut area, production, and yield over time. [37] The autoencoder was initially utilized for dimensionality reduction in multivariate time series, resulting in a compressed lower-dimensional latent representation. [38] These minimal illustrations are transferred to the LSTM method, which searches for long-term patterns in data by modelling temporal relationships and doing trend analysis. The trend analysis that uses the autoencoder-LSTM architecture combines the best parts of both models to work well with complicated, multivariate time series information about groundnut area, production, and yield in AP.

The AELSTM approach is specifically built to solve these problems, unlike other machine learning models that generally assume linear correlations and have trouble capturing complicated temporal relationships in multivariate time series information. The autoencoder portion does an adequate job of reducing dimensionality and filtering out noise while discarding crucial data. The LSTM network, on the other hand, is fantastic at depicting nonlinear trends and long-term periods. The AELSTM is better at trend analysis than typical ML approaches because it combines these two things. Typical ML methods often need a lot of feature design and are not able to completely capture shifting agricultural trends.

Figure 5 illustrates the way the AELSTM is designed. Initially, the input data goes through an autoencoder. The encoder minimizes the input within a smaller latent space, and the decoder puts the original input back together from this smaller version. After that, the LSTM network gets a description of the latent space, which tells it what the most important parts of the input are. The LSTM uses its memory cells and gates (forget, input, and output) to look at these parts in order and figure out how they work together. The LSTM output shows how trend analysis works. In the first step, move pre-processed time series information through the autoencoder's input layer. The encoder network uses nonlinear transformations to find important features and patterns while getting rid of noise and unnecessary data. It does this by decreasing the total number of dimensions via hidden layers, shown in Equation 4.

$$x = f_1(wy + b) \quad (4)$$

Here, y is the pre-processed data, x represents the hidden layer, f_1 is the activation function, w denotes the weight matrix, and b is the bias vector. The bottleneck layer stores a shorter version of the input data and important patterns for trend modelling at the LSTM stage. The decoder network then uses this mathematical model to bind the beginning of the input again, preserving the significant details shown in Equation 5.

$$\hat{y} = f_2\left(w\acute{x} + \acute{b}\right) \quad (5)$$

In this case, w' plus b' are weights as well as bias of the output layer, f_2 is the activation function of the decoder, and the hidden phase is transferred via construction $\hat{y}$. The LSTM gets the compressed, noise-filtered latent forms to use trend analysis and time-based simulations.

The LSTM takes in a series of vectors that show how the important parts of the time series information shift periodically. When the LSTM forget gate compares the present input to the last hidden state, this gets rid of data that is not useful or does not last long. Equation 6 shows how it gets rid of long-term trends in agricultural data that are not important while keeping the most important ones.

$$f_t = \sigma\left(w_f[h_{t-1}, x_t] + b_f\right) \quad (6)$$

Here, σ is the sigmoid activation function, f_t is the forget gate, w_f is the weight matrix of the forget gate, x_t is the input vector at the present time phase, $h_{(t-1)}$ is the hidden state from the prior phase t-1, and b_f is the bias vector of the forget state. The LSTM input phase allows a sigmoid activation function for deciding what to keep in memory. This helps the model learn new patterns, like yearly groundnut production statistics, and improves its ability to predict future patterns, demonstrated in Equation 7.

$$i_t = \sigma(w_i[h_{t-1}, x_t]) + b_i \quad (7)$$

In this case, i_t means the forget gate, where w_i is the weight matrix, and b_i is the bias vector. The output gate of the LSTM specifies how parts of learned trends, like long-term variations in groundnut yield, deserve findings as the hidden phase. LSTM achieves this by using a sigmoid activation to select the most important information and a tanh function to generate the final output, which accurately analyzes trends by eliminating short-term changes given in Equation 8.

$$o_t = \sigma(w_0[h_{t-1}, x_t] + b_0) \quad (8)$$

Here, o_t denotes the forget gate, w_0 is the weight matrix, and b_0 is the bias vector of the forget state. The LSTM uses these gates to look for long-term changes in area, production, and yield on groundnuts. The AELSTM method is very good at finding and modelling complicated, long-term trends in agricultural time-series data, which makes it very useful for trend analysis.

3.5. Hyperparameter Tuning

Hyperparameters of the Autoencoder and LSTM are exhibited in Tables 2 and 3, respectively.

Table 2. Autoencoder Hyperparameters

Hyperparameter	Range
Input window size	10 years
Encoder layers	1
Encoder neurons	32
Bottleneck size	8
Decoder symmetry	Yes
AE activation	tanh
AE dropout	0.1

Table 3. LSTM Hyperparameters

Hyperparameter	Range
LSTM layers	1
Hidden units	32
Recurrent dropout	0.1
Activation function	sigmoid

3.6. Benefits of Trend Analysis using AELSTM

The AELSTM method understands complicated patterns and long-term relationships, which makes predictions more accurate. Adding autoencoders makes it easier to cut down on noise and the number of dimensions. The result improves the data and makes the algorithm stronger. AELSTM remains superior to conventional statistical models in managing non-stationary agricultural data and identifying correlations among critical production variables. The results offer practical advice on policy development, crop management, and the extension of sustainable agriculture, while advancing the development of intelligent applications in agricultural statistics.

3.7. Novelty of the AELSTM Approach Compared to Statistical Methods

The suggested AELSTM framework is novel to address the problems that occur with traditional trend approaches. AELSTM method, on the other hand, is a completely data-driven technology. All of the linear, quadratic, cubic, and exponential frameworks use predefined functional forms and assume that relationships do not change over time. An autoencoder and LSTM work well together to reduce noise and identify features. The LSTM network also finds long-term changes and unusual patterns in agricultural data. This hybrid architecture makes things more stable as things change and makes predictions much more accurate.

4. Results and Discussion

The simulation findings of the suggested methodology are implemented in Python, and the performance metrics are described within this part. The findings of the proposed AELSTM approach are examined using conventional statistical trend algorithms and architectural base frameworks. The coefficient of determination, or R^2, is a statistical measure used with a trend analysis approach to determine the size of dependent factors defined by the independent factor. It demonstrates how effectively the model fits the data, as shown in Equation 9.

$$R^2 = 1 - \frac{\sum(a_i - y_i)^2}{\sum(a_i - x_i)^2} \tag{9}$$

Here, a_i is the actual observed value, y_i denotes the value predicted from the model, and x_i is the mean of the observed values. CAGR is the mean yearly increase of an investment or commercial metric over a period of time longer than a year.

This assumes that the amount invested expands at a stable, compounded rate each year. CAGR removes the impact of fluctuations and gives a distinct growth rate to demonstrate whether the value has declined over the years.

CAGR is required to define a more precise and reliable way to measure long-term changes in groundnut cultivation variables, including area, production, and yield. Annual percentage improvements are quite unstable and misleading because they are based on short-term changes. CAGR, on the other hand, provides a regular, compounded rate that demonstrates the genuine average yearly rate of change throughout the entire span of time. This enables researchers, policymakers, and agricultural officials to independently figure out the viability of groundnut farming and how it has changed over the years, as shown in Equation 10.

$$CAGR = \left(\frac{Ending\ Value}{Beginning\ Value}\right)^{\frac{1}{n}} - 1 \tag{10}$$

Table 4. Analysis of the proposed approach over statistical trend models

Methods	R^2 (Accuracy)		
	Area	**Production**	**Yield**
Linear	0.78	0.74	0.77
Quadratic	0.75	0.76	0.79
Cubic	0.73	0.78	0.74
Exponential	0.78	0.75	0.71
AELSTM (Proposed)	0.95	0.96	0.94

Table 5. Performance analysis of the proposed architecture-based models

Methods	R^2 (Accuracy)		
	Area	Production	Yield
Dense Autoencoder	0.87	0.88	0.86
Vanilla LSTM	0.89	0.90	0.88
Sequence-to-Sequence (Seq2Seq)	0.91	0.92	0.90
AELSTM (Proposed)	0.93	0.94	0.96

The R^2 results in Table 4 show how well different statistical models predict changes in area, production, and yield of groundnuts for AP. Standard methods such as quadratic, cubic, linear, and exponential techniques typically exhibit limited precision, R^2 merits spanning 0.71 to 0.79 for each variable. These algorithms cannot accurately capture the complicated and irregular time trends that are frequent in long-term agricultural observations. The AELSTM method is suggested as much better than these conventional approaches. For area, the R^2 value is 0.95; for production, it is 0.96; and for yield, it is 0.94. The model is better since it blends lower dimensions with the autoencoder and time-based pattern acquisition with LSTM. The hybrid design enables the algorithm to determine both long-term dependencies and sudden changes better than static curve-fitting methods.

R^2 is a way to measure determined variance, the range of change in the dependent variable explained by the approach. Because of this, it was a useful way to measure how well the model fit the trend. R^2 systematically compares different modelling methods, such as deep learning models and traditional statistical models, even if they are set up in different ways. Higher R^2 values are more accurate, which makes it easier for policymakers and researchers to understand. Table 4 shows how the proposed AELSTM compares to statistical trend models such as the linear, quadratic, cubic, and exponential methods. The linear trend model was selected because it has a constant rate of variation over time and functions as a primary benchmark for detecting long-term directional trends in area, production, and yield. The quadratic trend approach was chosen because it reveals some non-linear behaviour, including trends speeding up or slowing down. This is commonly due to new technology or changes in the policy. The cubic trend method was used to look at more complex growth patterns and possible turning points in agricultural farming systems. The Exponential Trend Model was chosen to show how multiplicative growth works. This phenomenon is often linked to yield gains that come from using resources wisely, mechanizing tasks, and using new methods. Table 5 shows how the proposed AELSTM is different from deep learning architectures like the dense autoencoder, vanilla LSTM, and sequence-to-sequence (Seq2Seq) algorithms. These models are acceptable, but the AELSTM is better because it combines the best parts of extracted features (autoencoder) and sequence estimation (LSTM) into one method. This combination enhances our understanding of structural trends and reduces the probability of noise affecting AELSTM. Consequently, it attains R^2 values of 0.95, 0.96, and 0.94 for area, production, and yield, respectively. These results suggest hybrid designs to help with difficult information about farming and the environment. Actual facts and fundamental studies in the literature substantiate the greater effectiveness of AELSTM.

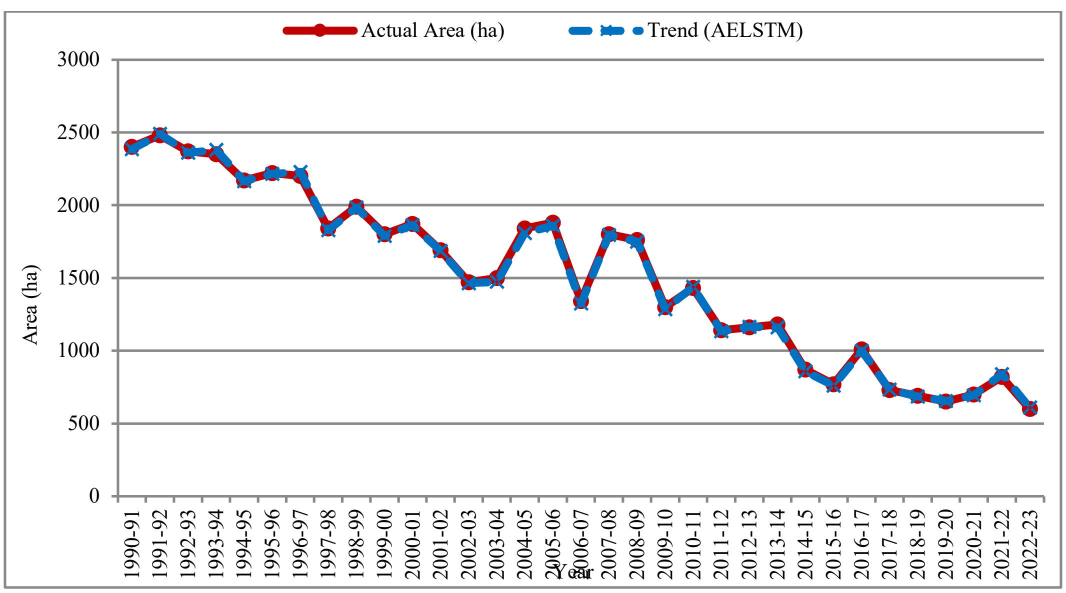

Fig. 6 Analysis of Actual and Analyzed Groundnut Area via the proposed model

Figure 6 compares the real area to the area that the AELSTM model predicted. It also shows how the area (hectares) has changed from 1990-91 to 2022-23. The model does a strong job of finding the underlying trend because the actual and expected values are close.

Over the progress of several decades, the area under cultivation has generally been going down, with some ups and downs along the way. These changes indicate that either farming methods have evolved or external factors have impacted the land being cultivated.

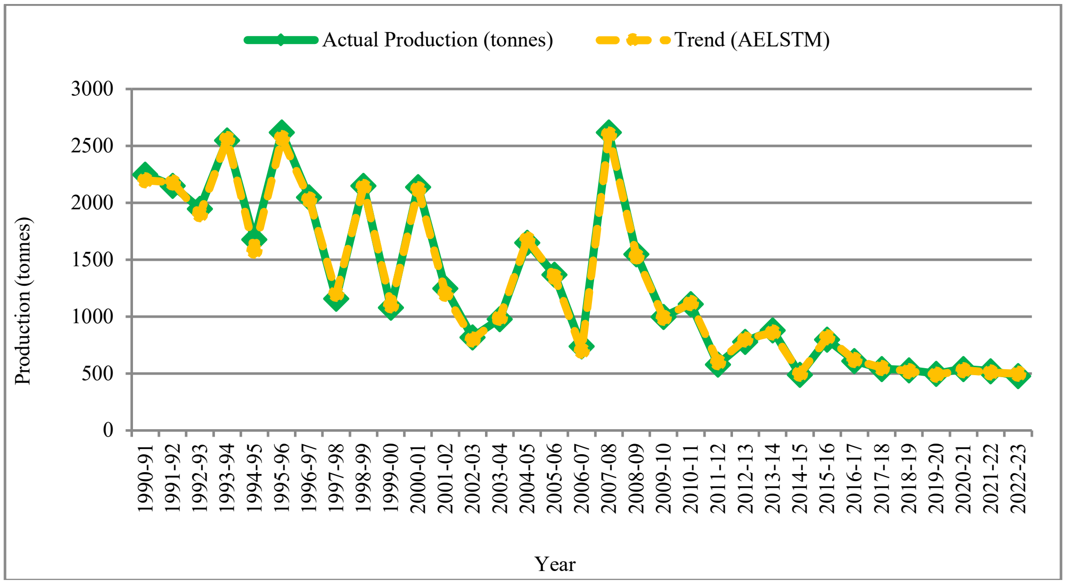

Fig. 7 Analysis of actual and analyzed Groundnut Production via the proposed model

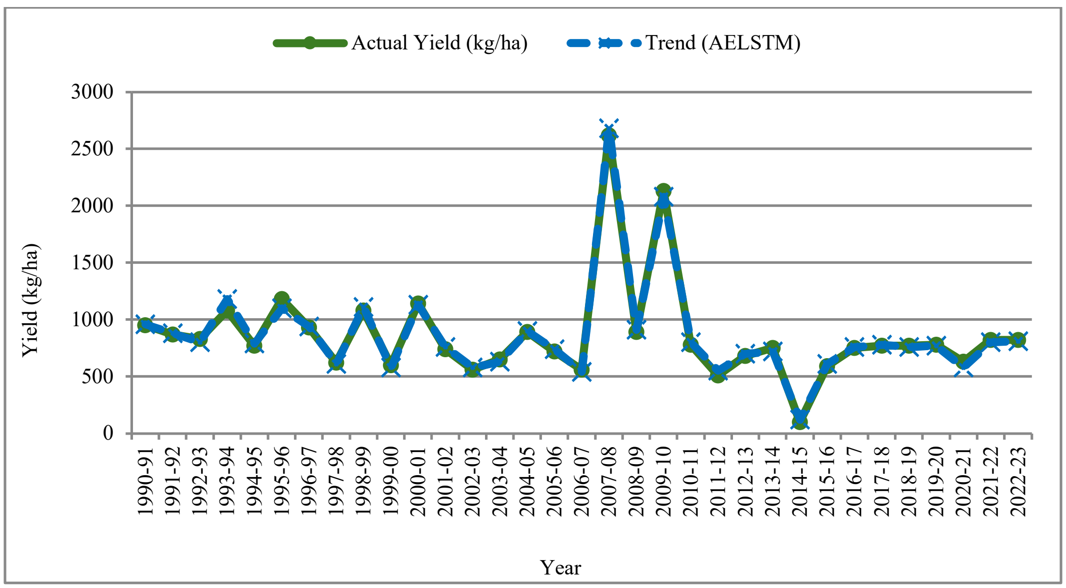

Fig. 8 Analysis of the actual and analyzed Groundnut Yield via the proposed model

Figure 7 shows the production (tonnes) during the same time. It contrasts the real numbers with the values that the model anticipated. The anticipated production nearly matches the actual production, and the model does a satisfactory job of capturing the unforeseen fluctuations experienced in certain periods. The anticipated production nearly matches the actual production, and the AELSTM model does an adequate job of capturing the unexpected fluctuations in output that happened in the mentioned periods. Figure 8 summarizes the trend analysis of yield (kg/ha), which compares actual yield to the projected yield. The AELSTM technique forecasts almost correctly, which shows that it is quite proficient at predicting yields. There are many big ups and downs in the yield analysis, especially in 2007-08 and 2012-13. The algorithm does a competent job of finding patterns. The reality that the actual and anticipated outcomes are actually very similar on each of three parameters (area, production, and yield) indicates that the AELSTM method works well for looking at trends in agricultural data over time. Table 6 offers research on CAGR with growing groundnuts in AP from 1990–91 to 2022–23. It indicates that important measures have been going down continuously for a long period. The area used to grow groundnuts has shrunk by an average of -3.97% each year, while the production has shrunk by an average of -4.57%. This illustrates that both the amount of land used and the amount of production have gone down a lot.

The yield, which usually means better farming practices or technology, has a CAGR of -0.79%, which means that the yield has gone down somewhat. CAGR is important because it presents a clear, standardized view of the direction and size of long-term trends, which is more than just changes from year to year. This statistic improves the thoroughness of the inquiry by evaluating the decrease rates. This indicator helps planners and policymakers realize that action is needed and come up with targeted plans to change those patterns.

Table 6. CAGR analysis

Variable	CAGR (1990-91 to 2022-23)
Area (ha)	-3.9 % Per Year
Production (t)	-4.5 % Per Year
Yield (kg/ha)	-0.7 % Per Year

4.1. Discussion

The suggested AELSTM method for looking at changes in the number of groundnuts grown, the amount of output, and the amount of yield in AP has many benefits over traditional statistical methods. The suggested method uses autoencoders to reduce dimensionality and LSTM networks to look at temporal trends in order to find complicated patterns in time series agricultural data. The initial stage of the KF processing phase ensures the correct handling of missing values and noise. This presents reliable and normalized data used to identify trends. The AELSTM method works well because it has R^2 values of 0.95, 0.96, and 0.94 for area, production, and yield, respectively. This evidence shows that it is possible to accurately predict long-term changes and trends in agricultural data.

The AELSTM framework helps put data-driven policies into action, so they keep growing. The AELSTM model correctly shows both little and large changes in groundnut production and yield in AP. The AELSTM model works better than earlier statistical models like Linear, Quadratic, Cubic, and Exponential in Table 4 and architecture-based models like Dense Autoencoder, Vanilla LSTM, and Sequence-to-Sequence (Seq2Seq) in Table 5.

The AELSTM model has far higher R^2 ratings for all three metrics: area, production, and yield. The sensitivity analysis indicates that the AELSTM model largely employs historical data and factors that vary over time. This makes it more accurate and trustworthy. Finding significant parts of models makes them easier to grasp and helps policymakers make changes that will improve the area, increase production efficiency, and raise agricultural yields. The AELSTM model changes the importance of features in real time and finds nonlinear relationships between input parameters.

4.2. Analysis of Actual and Analyzed Groundnut Area, Production, and Yield using AELSTM

The real and calculated groundnut area metrics in the AELSTM model are very similar, which means that the model does a competent job of discovering basic patterns over time. The autoencoder phase reduces noise in data and makes features easier to see, which makes area trends more accurate and trustworthy. The framework's ability to adjust basic factors is shown by little changes that happen after rapid changes in policy. The results indicate that AELSTM is superior to ordinary trend forecast models for accurately measuring the area of groundnuts and making judgments about cultivation.

4.3. Policy Implications

The outcome of this experiment offers meaningful policy insights to address the challenges faced by farmers. The AELSTM method is useful for discovering patterns in the groundnut area, production, and yield when using data-driven methods. Policymakers can set clear goals for controlling land use, resource distribution, and diversifying farming methods when they can precisely and on time predict changes in agricultural land and production. When the market is unstable or the environment changes, people can make judgments ahead of time since the model finds unique patterns and long-term connections. Moreover, accurate production estimates help set the lowest prices for help, make it easier to plan when to acquire things, and ensure that oil and food crops are stable. In general, applying AELSTM-based analytics helps agricultural policies that are based on data and make farming more sustainable, productive, and flexible.

4.4. Limitations

The research relies exclusively on secondary data sourced from Indiastat, which introduces mistakes, aggregation errors, and alterations, thereby affecting model precision.

- Only the area, production, and yield parameters were taken into account.
- The AELSTM approach did not include factors such as climate, socio-economics, and government policies.
- R^2, the precision metric for performance assessment, just looks at trend illustration and does not accurately show how predicted errors are spread out.

5. Conclusion

The AELSTM model is an excellent tool to see how the area, production, and yield of groundnuts in AP are changing over time. Trend analysis is better than prior methods because it works with big, complicated datasets, makes them smaller, and shows how things change over time. The R^2 values for area, production, and yield of the AELSTM model are 0.95, 0.96, and 0.94, respectively. This shows that it works better than typical statistical frameworks and architectural base techniques. We demonstrate the hybrid deep learning AELSTM approach's ability to find complicated patterns and modify them to make decisions about farming policy. It helps farmers take care of their crops, use their resources more wisely, and increase the area's output. Future research will concentrate on expanding the dataset to incorporate extended timeframes, hence improving trend reliability. The model potentially performs a better job of illustrating changes in the area, production, and yield of groundnuts, including important factors like climate and socioeconomic factors.

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