Research Article

Study of agronomic exports based on deep learning and Data mining

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Abstract

Exports of agronomic products are a major source of income for many countries across the world. Import, export, and domestic usage data, as well as the adjustments to production and marketing that follow, may all be better predicted using monthly Agronomic Export Forecasting. To better anticipate the growth and drop of Agronomic exportations, this study presents a new approach called Agronomic exports time series-longshortterm memory. An algorithm is used to train vectors of words by dividing words into groups and then using Term Frequency -Inverse Document Frequency/word cloud to studyinformational keywords. This study investigates whether the AETS-LSTM model can effectively use the purchasing managers' index (PMI) of everyindustries to anticipate the increase and fall of agronomic exports. A study of the PMI principles in the financial and insurance industries found that using keyword vectors increased the accuracy of predicting growth and decline in Agronomic exports by 82.61%. Combining electrical and optical keywords improves its effectiveness in these categories.. Thus, agribusiness operators and policymakers will be able to use the recommended approach for a more accurate assessment of local and international output and sales.

KeywordsPurchasing managers' index, Artificial Intelligence, Long short-term memory, Controller, Exports, Data mining.

1 Introduction

Resources and infrastructure for artificial intelligence have grown, and can now be applied to a wide range of domains, including time series, image processing and audio signal analysis[1]. This allows for a wide range of problems to be addressed. In the context of time series analysis, models of LSTM are typically used, despite the fact that time series are widely used across numerous disciplines. Using time series, [2]developed a model for detecting aberrant behaviour in controller area network (CAN) bus tampering attacks. The overall local grid transmission losses were calculated by [3]based on local meteorological data. According to [4], the no of COVID-19 expiries in 10 foremost nations was predicted using time-series approaches. Normal language dealing out and data translation based on supervised learning was proposed by [5]to manage and analyse a wide range of data.

Although agriculture was a major part of India's early economic growth, its relevance has waned as the country shifts to a technologically advanced and industrially oriented economy[6]. Since food security and resource sustainability are of utmost importance, the administration has started to pay more consideration to the growth of agriculture-related businesses. India has a large amount of arable land, and farmers focus on producing high-value agricultural goods rather than large-scale businesses[7]. As a result, exports have gradually increased, and the government intends to keep this trend going so that export earnings may more accurately represent actual earnings and help to balance localformation and sales[8]. Internet-based news sources deliver rapid and handy information on what's going on at home and across the world at the press of a button. Industrial stock prices can be accurately predicted using purchasing manager indices, according to [9], [10] were able to estimate agricultural product prices using news about climate change and oil prices. Agricultural production has been found to be affected by global warming, according to [11], [12]analysis of the overall farm productivity. In order to make predictions about coal mining accidents, [13], [14]employed several PMI as auxiliary variables. It was proposed by Su et al. that the prices of agricultural items and oil are linked in a causal fashion that is both positive and reciprocal. It was argued that China's Agronomic export revenues to ASEAN countries were significantly affected by the global financial crisis and shared boundaries[15]. It is the goal of this research to find out if news about global climate change, energy costs, and other pertinent topics, as well as changes in PMI for specific industries, have an impact on Taiwan's agricultural exports . Future agricultural export patterns may be predicted using an AETS-LSTM deep learning model, which is adjusted for features and weight factors of the learning board column. Here is a breakdown of how this research will proceed: LSTM, data mining, and principal component analysis are examined in Segment 2. Segment 3 provides an overview of the study's design and methodology[16]. Finally, Section 5 sums up the findings.

LSTM

The three control gates that make up LSTM are input, for-get, and output. To decide if a new LSTM must be activated, the input gate utilizes the input and newly created memory cell values in an initiation function. Filtering or saving the current value in memory depends on whether or not it is new or the opposite of the existing value. It's up to the production gate to decide whether the present value should be additional to the production or not. The Sigmoid approach is commonly used to figure out how the output valve would open and close when activated. If LSTM memory should be included in the output, the activation function tanh is employed. +1 indicates that long-term memory should be retained, whereas (-1) indicates that it is best to remove. Fig. 1 displays the LSTM planning, which is followed by Equation. (1) to (4), in order, after [17] and [18].

$$f_h = \sigma\left(w_f \cdot [h_{h-1}, x_h] + b_f\right) \tag{1}$$

$$i_h = \sigma(w_i \cdot [h_{h-1}, x_h] + b_i) \tag{2}$$

$$\widetilde{c_h} = \tanh\,(w_c \cdot [h_{h-1},, x_h] + b_c) \tag{3}$$

$$C_h = f_h * c_{h-1} + i_h * \widetilde{C_h} \tag{4}$$

$$O_h = \sigma(w_O[h_{h-1}, x_h] + b_0) \qquad (5)$$

$$h_h = O_h * \tanh(C_h) \qquad (6)$$

Whereas,

f_h,i_h -forget, input value respectively
O_h -output value,
$\tilde{c_h}$ -memory cell candidate,
h_{h-1} -current output value, and
x_h - input value.
w_i, w_c, w_o, w_f − the weight matrix and
b_i, b_c, b_o, b_f-the deviation vector.
C_h -storage unit
σ -Sigmoid activation function.

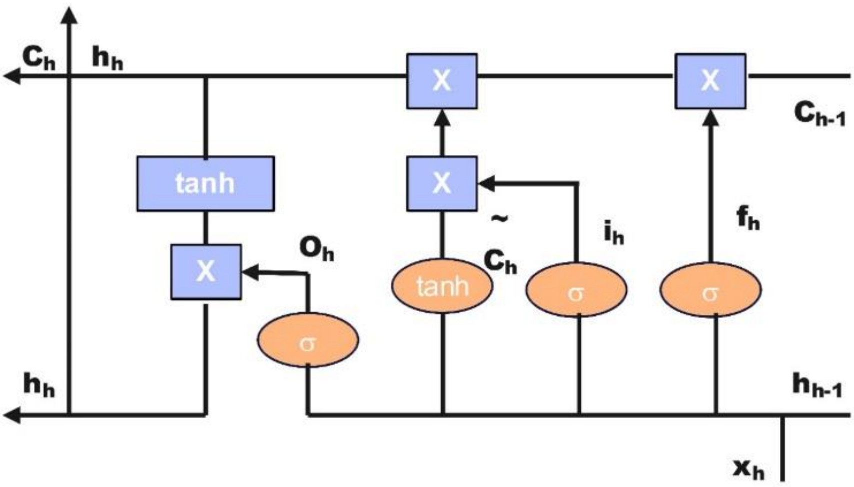

Fig. 1 Long short-term memory Architecture

For voltage forecasting, [19] developed an approach that uses a nonlinear LSTM algorithm. An LSTM model created by [20] can forecast the performance of stepped solar distillers and conventional distillers. When employing performance metrics like MSE, PNSR, RMSE, and NRMSE for COVID-19 forecasting, the final results showed that LSTM was more accurate than any other method in the countries studied. Using input and output data, [21], [22]developed a system model that could predict the chemical composition of sinter based on input and output data. Using an LSTM framework, [23]suggested a method for forecasting fog based on hourly meteorological data. The LSTM architecture was thought to be more successful than typical machine learning models in this case. At [24], [25]suggestion, the researchers employed a grid search algorithm to optimize the hyperparameters of their suggested Conv-LSTM diabetes classifier. CNN and LSTM were combined by [26]to extract meaningful characteristics for assessment, and the results were promising. Within the test's prediction range, they showed that their suggested model beat many other LSTM and CNN models. For gear life prediction, [27], [28]developed an ON-Long short-term memoryexperiment that was compared to the performance of other models including LSTM, GRU, DLSTM, and DNN. With regards to both short and long term prediction accuracy, our ON-LSTM model was the most accurate.

Data mining

As a result, data mining methods are incapable to discover clearly identifiable texts in lengthy or short paragraphs, in spite of the fact that they are clearly understandable in daily life. IDF and TF (term frequency) make up the typical statistical calculation approach known as TF-IDF (inverse document frequency). As shown in Eq. 7, TF refers to frequency, whereas IDF is a metric used to determine the overall value of a word, as shown in Eq. 8. (8). Common phrases are removed while crucial ones are retained using the TF-IDF method, same as in Equation (9).

$$IDF_i = \log\left(\frac{D}{d_i}\right) \qquad (7)$$

whereas

D - All news content

d_i - Noof words. The denominator is 0 if a word is absent from the text of the news report, hence$t_i + 1$ is usuallyemployed.

$$TFIDF_{i,j} = TF_{i,j} \times IDF_i \qquad (8)$$

TF-IDF can be used to assess the frequency of certain terms and phrases in a segment of news content.

In order to convey the meaning of words and phrases, Word2Vec is a technique that converts words into vectors that transmit their sense, such as synonyms, antonyms, and analogies. As a result of this, Word2Vec's significance has increased. Each word or phrase was assigned its own unique vector by [29], who used massive quantities of text data to construct a vector for each word or phrase. Words with comparable meanings will be closer together once they have been embedded in a space. CBOW and Skip-gram are the two most prevalent Word2Vec models. For example, a skip-gram utilises a words to forecast the framework, whereas CBOW employes a specific context to forecast the contribution. The CBOW and Skip-gram model designs are depicted in Figures 2 and 3, respectively.

Cuckoo Search-eXtreme gradient boosting was proposed by [30]. and optimised for airline recommendation. A network-based aspect-aware sparse self-attentive model (2021 b) was also suggested, and this model is capable of accurately predicting customerreferenceconclusions in advance. Yen et al. conducted text exploration and predicted future financial performance using language from internet news and stock forums. Using data mining, [31]suggested to identify cyberbullying by analysing social network messages. Studies on academic publications' information value, breadth, and trends were examined using keyword and citation data mined by Jung and Lee. The gravity search algorithm (GSA) was used to optimise multiple expression goals in order to develop succinct social media summaries, which Mosa suggested as a recombination problem for large-scale social media data mining. Using data mining techniques, [32]collected and analysed public comments on Weibo in order to better understand public attitude about an urban garbage categorization strategy. A four-step approach presented by [33]. A convolutional neural network (CNN) technique, followed by a word co-occurrence network (WCN), which builds the linkages among dangers, and lastly a quantitative keyword analysis utilising word cloud systems to produce an outline of such threats, provides executives with fresh information. Research articles mentioned in recent agricultural research publications were subjected to data mining by Drury and Roche, who were looking for issues and possible solutions.

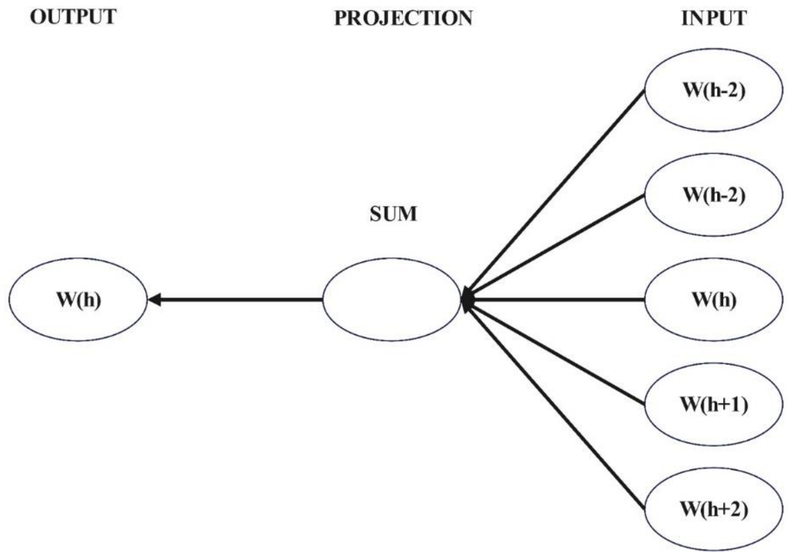

Figure . 2Model forCBOW

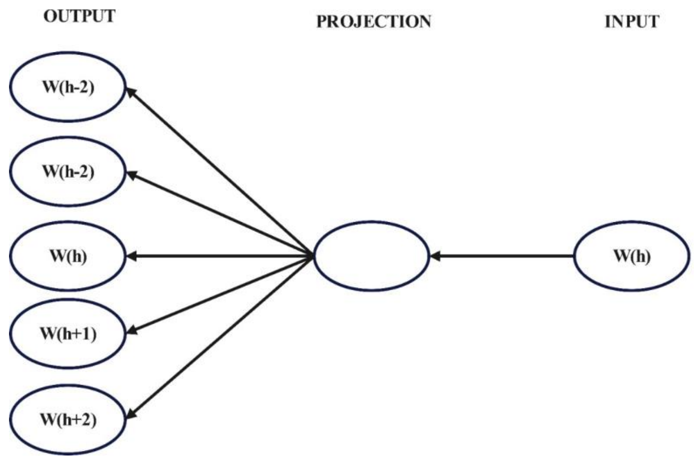

Figure. 3Model Skip-gram

Principal component analysis

As a common unsupervised learning linear transformation approach, principal component analysis (PCA) allows the original data to be transformed into many different expressions while also enabling data processing. PCA is a widely-used method. PCA minimises computing time and memory space needs when high-dimensional data is reduced to lower-dimensional data, making it easier to store and analyse. A linear transformation of the data using Eq. (1) requires independent variables, whereas Eq. (11) is an example of how to identify independent variables in the data using Eq. (12), where S is the primary component of variance.

$$y_1 = v_{11}x_1 + v_{12}x_2 + \cdots + v_{1q}x_q \tag{9}$$

$$y_2 = v_{21}x_1 + v_{22}x_2 + \cdots + v_{2q}x_q \tag{10}$$

$$y_q = v_{q1}x_1 + v_{q2}x_2 + \cdots + v_{qq}x_q \tag{11}$$

$$\lambda v = Av$$

$$\mathrm{S} = \frac{\lambda_1+\lambda_2+\cdots+\lambda_r}{\lambda_1+\lambda_2+\lambda_3+\cdots+\lambda_q} * 100\% \tag{12}$$

It was proposed by [34] and [35] that a novel multivariate approach based on PCA and PLS could be used to assess statistically the impact of the steadiness of inverse and perovskites. Classifying COVID-19's distribution in the US and the UK was made possible by PCA by [36]. PCA was used by [37]to classify vesicles and bronchi more simply, economically, and sensitively. [38]discovered high-dimension data influences the procedure's computation period and proposed a novel technique to minimise data volume utilising the Apache Spark platform and major component examination. By reducing data dimensionality, [39], [40]asserted, PCA might help researchers better understand and utilise their data, which would lead to less information being lost. As more information is gathered, PCA is able to adapt to the needs of the data it analyses.

Research design and process

Researchers in this study are working with hardware and software that is divided into two distinct layers. On an i7 processor with 24GB of Random Access Memory and a GeForce GTX1650Ti graphics card, Windows 10 64-bit is installed. Develop with Python 3.6.
Internet news, industry-specific metrics, and agricultural exports are all tracked using web crawlers in this study. Training the LSTM model is one of many steps in the process. It's evident from the diagram in Figure 4.

Collection of International News from 2016 to 2021

ETtoday's international news section is crawled using Web crawlers to collect all international news reports from January 1, 2016, to December 31, 2021, using HTML tags to strainer all news information by means of search phrases such agricultural, petroleum, climate and other relevant themes.

Utilizing Jieba for international news separation

Jieba word separation was used to handle the global news content data for this study in order to aid subsequent data annotation and smooth out the overall computation and structure.

Using TF-IDF findkeywords

An article's top 10 most important keywords are then determined by applying the TF-IDF algorithm after Jieba segmentation.

Utilizing Word2Vec conversion words to word vectors

The Word2Vec approach vectorizes words after Jieba segmentation, allowing the computation of word similarity. All of the tested and interpretable word vectors have the same dimensions of 100, 200, and 300, respectively. CBOW is used to train the Word2Vec feature vector, which has been set to 100 dimensions.

Analysis of word clouds sorted by date

For each month, keywords were broken down into categories, and the ten most important words were selected using word cloud analysis.

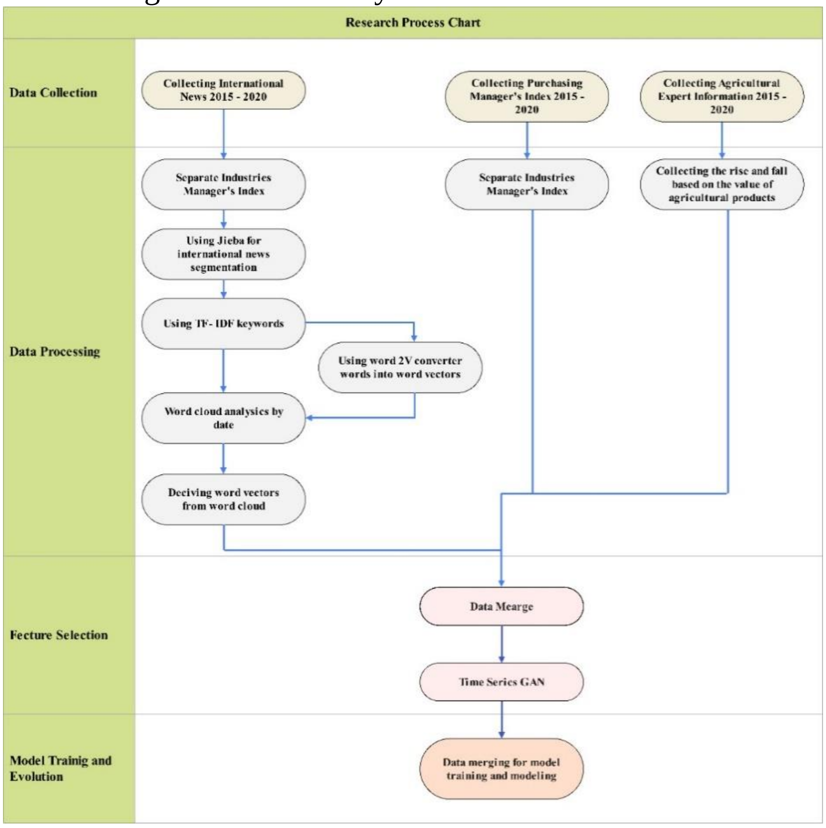

Fig. 4Research process chart

Originating word vectors from word cloud

The proficient Word2Vec model was then used to extract the word vectors for 10 important terms.

Data dimensionality deductionby PCA

PCA is used to decrease the dimensions of the resulting word vectors to 55, with an interpretability rate of 90 %. As a result, the word count should be decreased from 1000 to 55 for the purposes of this study.

Collection of PMI 2016—2021

The Business Indicators Database Web site provides access to the PMI for 2016 to 2021.

Purchasing managers' indexes from various industries

A range of industries, including chemicals, biologicals, medical devices, transportation equipment, wholesale and retail financial services, and insurance, have manufacturing and non-manufacturing indexes. foodstuffs and clothing the essentials educational and professional broadcasting in the sciences and technology the exchange of ideas and information

Calculating the increase and decrease in agricultural product values

By deducting the preceding month's total export value, the researchers in this study were able to determine monthly changes in total export value.

Merging of Data

Data from agricultural export variations, the PMI to individual industry and industry outlooks for the subsequent6 months were combined with the 55-dimensional PCA in this study.

Time-series GAN

The informationsince 2016 to 2019 isn't enough to make meaningful inferences. This study employed time-series GAN to produce actual samples from both real and synthetic data, following the work of Yoon et al. and providing enough of information for working out.

Model training and modelling are aided by data merging

To develop the AETS-LSTM model, we'll require the following data: swings in agronomic exports, 55-dimension words to next PCA, the PMI for each sector, and a six-month forecast for each industry. Changes in exports of agronomic products during the next month are the output criterion. Following the time-series GAN method, a training set of data from 2016 to 2019 was employed. Data from 2020 to 2021 is used in the test. According to Srivastava et al., overfitting can be alleviated by using dropout, which is independent of each hidden layer neuron and iteration. Both size and location will be critical considerations. For instance, if the value is set to a number that is too large, the model will be unable to learn the training features. A value that is too little will result in model overfitting during training, which will result in Dropout.

Experimental results and evaluation of performance

The AETS-LSTM model predicts agricultural exports in each industry's PMI, which was previously suggested. More accurate agricultural export forecasts are provided by industries in the chemical and medical, lodging/food service; finance, insurance and basic resources; education; proficient; scientific; and broadcasting/dataindustry than by those in the other industries. Models that incorporate the PMI of individual industry and keyword vectors are used in this study to compare and evaluate the results. For anticipating changes in exports, a number of metrics are used to measure the accuracy and precision of the forecasts, as shown in Table 2 and Figure 5. All additional industries did well with AETS-LSTM models, with the exemption of lodging and food provision and building and real estate. Most of the performance evaluation findings may be attributed to the financial and insurance businesses, which have a forecast accuracy of 82.61 %, which is higher than that of other industries.

Estimated results for productions, including banking, insurance, transport, textiles, food, electrical and mechanical sectors were compared using projected AETS-LSTM model and neural network/SVM model. Agronomic exports' growth and decline may be accurately predicted using the AETS-LSTM model, as shown in Figure 6.

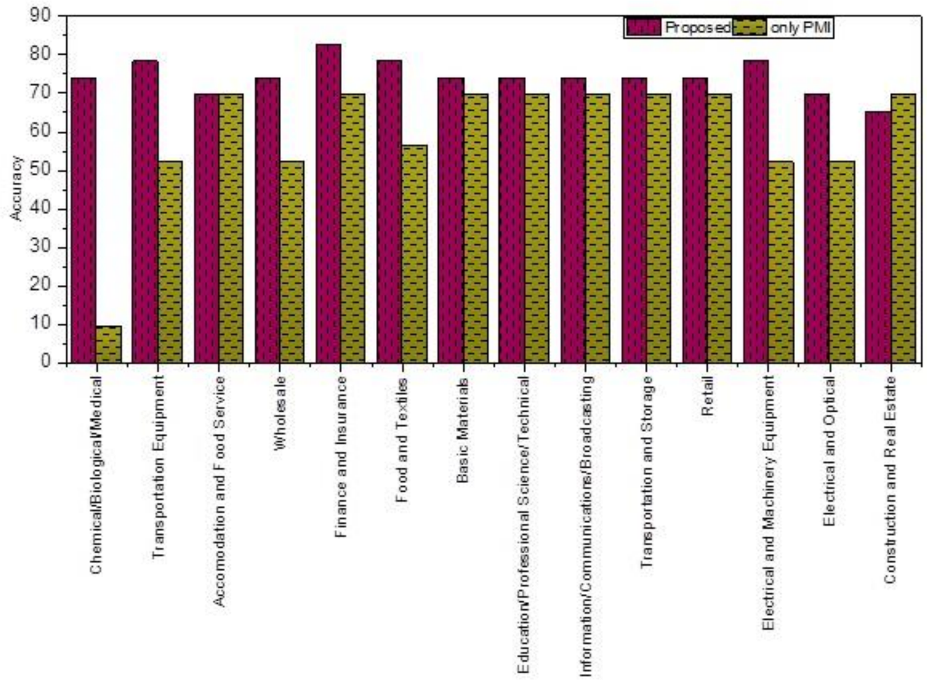

Fig. 5A comparison between the predictive power of using both keyword vectors and PMI alone

Table 1.ModelFactors

Factor Name	**Factor Value**
LSTM Layer	2 Layers
Activation Role	LSTM Layer
Output Layer	softmax
Dropout	0.2
Parameter Settings	Loss Function:
Optimizer	Adam
Output Layer	1 Layer
Regularizer	0.0001

Table 2Assessment of several sectors' predictive performance indicators

Industries	**Precision (%)**	**Recall (%)**	**f-score (%)**	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**
Chemical/Biological/Medical	78.24	64.16	69.27	64.78	84.12	74.02
Transportations Equipment	86.98	64.02	84.16	64.75	92.48	79.62
Accommodation and Food Service	69.14	64.42	65.67	64.28	76.19	70.42
Wholesale	78.18	64.14	69.18	64.12	84.27	72.28
Finance and insurance	82.19	82.19	82.19	82.19	84.24	83.19
Foods and Textiles	79.98	73.14	77.26	73.71	84.16	79.14
Basic Materials	73.16	73.16	73.16	73.16	76.12	74.21
Educations/Professional Science/Technical	78.16	64.76	69.98	64.73	84.13	74.26
Information/Communications/Broadcasting	78.98	64.45	69.98	64.73	84.13	74.26
Transportations and Storage	78.98	63.64	69.98	64.73	84.13	74.26
Retail	78.98	63.64	69.98	64.73	84.13	74.26
Electrical and Machineries Equipment	88.24	63.64	74.18	64.73	92.16	79.16
Electrical and Optical	69.98	63.64	65.66	64.73	74.98	70.24
Constructions and Real Estate	67.71	55.46	59.16	53.87	74.98	64.16

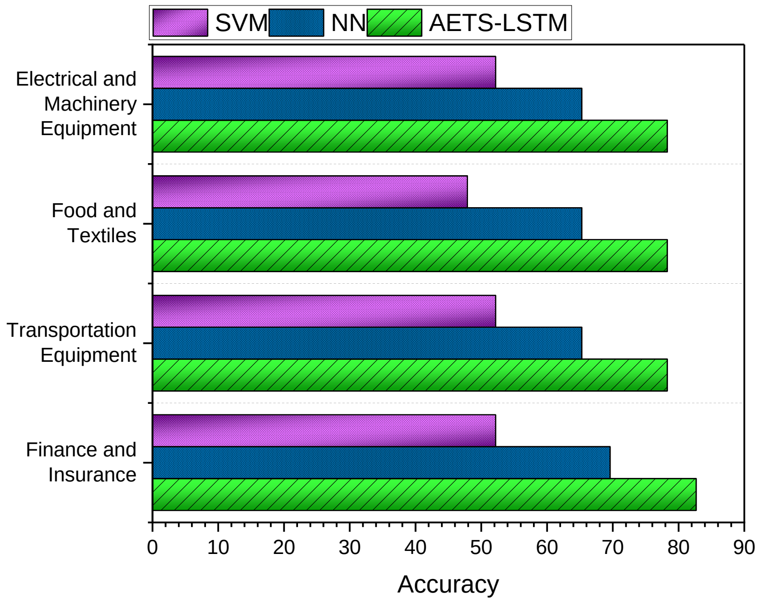

Fig. 6Evaluation of process accuracy for the topmost4 industries

5 Conclusion

The purpose of this study is to develop a novel AETS-LSTM model for forecasting agronomic export patterns. Numerous variables, include news contented, climatic changeand other industry PMIs, all influence agriculture export patterns. Few to no studies have been conducted on the effect of news content and PMI tendencies on agriculture. The findings of the experiments reveal that combining PMI data from the financial and insurance sectors with keyword vectors can enhance the accuracy of predicting the growth and drop of agricultural exports by 82.62%. But when it comes to forecasting for transportation and storage equipment as well as wholesale and financial services such as insurance and finance as well as food and textiles as well as education/professional science/technical forecasting as well as information and communication technologies such as broadcasting, it is impossible to combine keyword vectors to improve accuracy. Agronomic exports are rising and falling on a monthly basis, and our study can help agribusiness operators, policymakers, and others better understand the fluctuations in these exports.

A limited amount of agricultural export statistics can be viewed each month and privacy restrictions prohibit access to material that is not accessible openly, like news articles and Open Data sites. The accuracy of feature predictions is hampered by a lack of data. The current research only looks at exports of agronomic products, but the model framework might be used to other sorts of exports in the future, expanding on the existing findings.

References

[1] Z. Wu, Y. Zhang, Q. Chen, and H. Wang, "Attitude of Chinese public towards municipal solid waste sorting policy: A text mining study," *Sci. Total Environ.*, vol. 756, 2021, doi: 10.1016/j.scitotenv.2020.142674.

[2] M. Boubchir and H. Aourag, "Materials genome project: The application of principal component analysis to the formability of perovskites and inverse perovskites,"

Comput. Condens. Matter, vol. 24, 2020, doi: 10.1016/j.cocom.2020.e00495.
[3] Y. Chen, "Voltages prediction algorithm based on LSTM recurrent neural network," *Optik (Stuttg).*, vol. 220, 2020, doi: 10.1016/j.ijleo.2020.164869.
[4] J.-L. Xu and Y.-L. Hsu, "The Impact of News Sentiment Indicators on Agricultural Product Prices," *Comput. Econ.*, 2021, doi: 10.1007/s10614-021-10189-4.
[5] Y.-J. Choi, B.-J. Jeon, and H.-W. Kim, "Identification of key cyberbullies: A text mining and social network analysis approach," *Telemat. Informatics*, vol. 56, 2021, doi: 10.1016/j.tele.2020.101504.
[6] M. -F. Yen, Y. -P. Huang, L. -C. Yu, and Y. -L. Chen, "A Two-Dimensional Sentiment Analysis of Online Public Opinion and Future Financial Performance of Publicly Listed Companies," *Comput. Econ.*, 2021, doi: 10.1007/s10614-021-10111-y.
[7] H. Yan, Y. Qin, S. Xiang, Y. Wang, and H. Chen, "Long-term gear life prediction based on ordered neurons LSTM neural networks," *Meas. J. Int. Meas. Confed.*, vol. 165, 2020, doi: 10.1016/j.measurement.2020.108205.
[8] J. Yoon, D. Jarrett, and M. van der Schaar, "Time-series generative adversarial networks," in *Advances in Neural Information Processing Systems*, 2019, vol. 32.
[9] S. Chen and B. Gong, "Response and adaptation of agriculture to climate change: Evidence from China," *J. Dev. Econ.*, vol. 148, 2021, doi: 10.1016/j.jdeveco.2020.102557.
[10] B. Drury and M. Roche, "A survey of the applications of text mining for agriculture," *Comput. Electron. Agric.*, vol. 163, 2019, doi: 10.1016/j.compag.2019.104864.
[11] A. H. Elsheikh, V. P. Katekar, O. L. Muskens, S. S. Deshmukh, M. A. Elaziz, and S. M. Dabour, "Utilization of LSTM neural network for water production forecasting of a stepped solar still with a corrugated absorber plate," *Process Saf. Environ. Prot.*, vol. 148, pp. 273–282, 2021, doi: 10.1016/j.psep.2020.09.068.
[12] D. García-Gil, S. Ramírez-Gallego, S. García, and F. Herrera, "Principal Components Analysis Random Discretization Ensemble for Big Data," *Knowledge-Based Syst.*, vol. 150, pp. 166–174, 2018, doi: 10.1016/j.knosys.2018.03.012.
[13] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997, doi: 10.1162/neco.1997.9.8.1735.
[14] P. K. Jain, E. A. Yekun, R. Pamula, and G. Srivastava, "Consumer recommendation prediction in online reviews using Cuckoo optimized machine learning models," *Comput. Electr. Eng.*, vol. 95, 2021, doi: 10.1016/j.compeleceng.2021.107397.
[15] B. Zhong, X. Pan, P. E. D. Love, J. Sun, and C. Tao, "Hazard analysis: A deep learning and text mining framework for accident prevention," *Adv. Eng. Informatics*, vol. 46, 2020, doi: 10.1016/j.aei.2020.101152.
[16] S. Zeng, J. Gou, and L. Deng, "An antinoise sparse representation method for robust face recognition via joint l1 and l2 regularization," *Expert Syst. Appl.*, vol. 82, pp. 1–9, 2017, doi: 10.1016/j.eswa.2017.04.001.
[17] P. K. Jain, W. Quamer, R. Pamula, and V. Saravanan, "SpSAN: Sparse self-attentive network-based aspect-aware model for sentiment analysis," *J. Ambient Intell. Humaniz. Comput.*, 2021, doi: 10.1007/s12652-021-03436-x.
[18] P. K. Jain, R. Pamula, and E. A. Yekun, "A multi-label ensemble predicting model to service recommendation from social media contents," *J. Supercomput.*, 2021, doi: 10.1007/s11227-021-04087-7.
[19] P. K. Jain, R. Pamula, and G. Srivastava, "A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews," *Comput. Sci. Rev.*, vol. 41, 2021, doi: 10.1016/j.cosrev.2021.100413.
[20] H. Jung and B. G. Lee, "Research trends in text mining: Semantic network and main

path analysis of selected journals," *Expert Syst. Appl.*, vol. 162, 2020, doi: 10.1016/j.eswa.2020.113851.

[21] I. T. Jollife and J. Cadima, "Principal component analysis: A review and recent developments," *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.*, vol. 374, no. 2065, 2016, doi: 10.1098/rsta.2015.0202.

[22] İ. Kırbaş, A. Sözen, A. D. Tuncer, and F. Ş. Kazancıoğlu, "Comparative analysis and forecasting of COVID-19 cases in various European countries with ARIMA, NARNN and LSTM approaches," *Chaos, Solitons and Fractals*, vol. 138, 2020, doi: 10.1016/j.chaos.2020.110015.

[23] Q. Liu, J. Liu, J. Gao, J. Wang, and J. Han, "An empirical study of early warning model on the number of coal mine accidents in China," *Saf. Sci.*, vol. 123, 2020, doi: 10.1016/j.ssci.2019.104559.

[24] M. A. Mosa, "A novel hybrid particle swarm optimization and gravitational search algorithm for multi-objective optimization of text mining," *Appl. Soft Comput. J.*, vol. 90, 2020, doi: 10.1016/j.asoc.2020.106189.

[25] S. Liu, X. Liu, Q. Lyu, and F. Li, "Comprehensive system based on a DNN and LSTM for predicting sinter composition," *Appl. Soft Comput. J.*, vol. 95, 2020, doi: 10.1016/j.asoc.2020.106574.

[26] M. R. Mahmoudi, M. H. Heydari, S. N. Qasem, A. Mosavi, and S. S. Band, "Principal component analysis to study the relations between the spread rates of COVID-19 in high risks countries," *Alexandria Eng. J.*, vol. 60, no. 1, pp. 457–464, 2021, doi: 10.1016/j.aej.2020.09.013.

[27] K.-C. Miao *et al.*, "Application of LSTM for short term fog forecasting based on meteorological elements," *Neurocomputing*, 2020, doi: 10.1016/j.neucom.2019.12.129.

[28] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," 2013.

[29] W. Quamer, P. K. Jain, A. Rai, V. Saravanan, R. Pamula, and C. Kumar, "SACNN: Self-attentive Convolutional Neural Network Model for Natural Language Inference," *ACM Trans. Asian Low-Resource Lang. Inf. Process.*, vol. 20, no. 3, 2021, doi: 10.1145/3426884.

[30] H. Qin, M. Yan, and H. Ji, "Application of Controller Area Network (CAN) bus anomaly detection based on time series prediction," *Veh. Commun.*, vol. 27, 2021, doi: 10.1016/j.vehcom.2020.100291.

[31] M. Rahman, D. Islam, R. J. Mukti, and I. Saha, "A deep learning approach based on convolutional LSTM for detecting diabetes," *Comput. Biol. Chem.*, vol. 88, 2020, doi: 10.1016/j.compbiolchem.2020.107329.

[32] V. Raj, A. Renjini, M. S. Swapna, S. Sreejyothi, and S. Sankararaman, "Nonlinear time series and principal component analyses: Potential diagnostic tools for COVID-19 auscultation," *Chaos, Solitons and Fractals*, vol. 140, 2020, doi: 10.1016/j.chaos.2020.110246.

[33] F. Shahid, A. Zameer, and M. Muneeb, "Predictions for COVID-19 with deep learning models of LSTM, GRU and Bi-LSTM," *Chaos, Solitons and Fractals*, vol. 140, 2020, doi: 10.1016/j.chaos.2020.110212.

[34] C. Wei Su, X.-Q. Wang, R. Tao, and L. Oana-Ramona, "Do oil prices drive agricultural commodity prices? Further evidence in a global bio-energy context," *Energy*, vol. 172, pp. 691–701, 2019, doi: 10.1016/j.energy.2019.02.028.

[35] Z.-L. SUN and X.-D. LI, "The trade margins of Chinese agricultural exports to ASEAN and their determinants," *J. Integr. Agric.*, vol. 17, no. 10, pp. 2356–2367,

2018, doi: 10.1016/S2095-3119(18)62084-2.
[36] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: A simple way to prevent neural networks from overfitting,” *J. Mach. Learn. Res.*, vol. 15, pp. 1929–1958, 2014.
[37] S. Tahvili, L. Hatvani, E. Ramentol, R. Pimentel, W. Afzal, and F. Herrera, “A novel methodology to classify test cases using natural language processing and imbalanced learning,” *Eng. Appl. Artif. Intell.*, vol. 95, 2020, doi: 10.1016/j.engappai.2020.103878.
[38] A. Tsantekidis, N. Passalis, A. Tefas, J. Kanniainen, M. Gabbouj, and A. Iosifidis, “Using Deep Learning for price prediction by exploiting stationary limit order book features,” *Appl. Soft Comput. J.*, vol. 93, 2020, doi: 10.1016/j.asoc.2020.106401.
[39] J. Tulensalo, J. Seppänen, and A. Ilin, “An LSTM model for power grid loss prediction,” *Electr. Power Syst. Res.*, vol. 189, 2020, doi: 10.1016/j.epsr.2020.106823.
[40] Y. Wei, L. Bai, K. Yang, and G. Wei, “Are industry-level indicators more helpful to forecast industrial stock volatility? Evidence from Chinese manufacturing purchasing managers index,” *J. Forecast.*, 2020, doi: 10.1002/for.2696.