NEURAL NETWORK APPROACH FOR PREDICTION OF CROP YIELD USING RNN, FEED FORWARD AND LSTM ALGORITHMS

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Abstract**:** In crop yield prediction is a major area of research, where the information about the suitable crop to cultivate will be very much useful for the farmers to cultivate. The crop yield prediction in agricultural helps to the farmers to know how much yield they are expect from the cultivation. It is also helps in minimizing the loss of the farmers when unfavourable condition occurs. The proposed work is to predict the yield of the crop based on the suitable crop parameters like Temperature Min, Temperature Max, Humidity, Wind speed, Pressure using neural network model. In this research paper, crop yields predictions were established using Feed Forward Neural Network and Recurrent Neural Network model which predict the crop yield. The performances of neural network models were evaluated using the metrics like Root Mean Square Error (RMSE) and Loss.

1. INTRODUCTION:

Indian economy relies heavily on the agricultural sector. Because agriculture is so dependent on weather conditions, every farmer has a vested interest in being able to accurately anticipate the amount of harvestable crop he may expect. There are several reasons at play, but a major one is that farmers no longer place a high value on plant health, fertiliser use, or crop yields. It's possible that farmers would benefit more from increased crop output if they had access to weather trade forecasts. Weather is the primary variable in crop forecasting since it directly affects plant growth and production. Predicting crop yields and addressing food safety issues in advance of planting may be challenging in years with insufficient precipitation or humidity. Predicting agricultural yields may be both a very helpful and highly challenging aspect of crop productivity. Therefore, it was necessary to investigate the varying climatic conditions in order to estimate the output of agricultural yields, both financially and otherwise. Predicting crop yields is crucial in order to maximise agricultural output. The efficiency of these methods has been, and will continue to be, enhanced by the evolution of several prediction models. Artificial neural networks (ANNs) with a feed-ahead and recurrent neural network are used to make the yield forecast.

2. LITURATURE SURVEY:

1)In February 2013, S. Li, S. Peng, W. Chen, and X. Lu published a paper titled "Income: Practical Land Monitoring in Precision Agriculture with Sensor Networks" in the journal "Computers and Communications."

The paper discusses the implementation and benefits of sensor networks for precise agricultural monitoring and management. A new age of study into farming and agriculture has begun with the advent of Wireless Sensor Networks (WSNs). The use of WSNs in modern agricultural software has increased dramatically. In this study, we evaluate the available WSN 11 packages and the specific issues and challenges associated with installing WSNs for modern agriculture. In order to focus on the 12 distinct requirements, a thorough analysis of the devices, sensors, and communication mechanisms related with WSNs in agricultural packages is performed in Section 13. We provide a wealth of case studies in order to thoroughly investigate the pre-existing solutions given in the literature 14 in many groups according to their design and execution associated aspects. WSN deployments for 15 distinct agricultural packages are analysed, from both the Indian and global perspectives. For the purpose of identifying the factors for growth and future orientations of labour using cutting-edge technology, we highlight the advantages and disadvantages of sixteen of these solutions.

2) In 2013, A. D. Jones, F. M. Ngure, G. Pelto, and S. L. Young published a comprehensive review titled "What Are We Assessing When We Measure Food Security? A Compendium and Review of Current Metrics" in the journal "Advances in Nutrition." The paper provides an overview and evaluation of existing metrics used to assess food security, examining the various dimensions and indicators involved in measuring food security.

Evaluating nutrition, health, and development programmes, as well as guiding government policy across many sectors, all need an accurate measurement of food safety. This includes early famine warning and global monitoring systems. The many methods and tools available for determining whether or not food is safe to eat add complexity to this crucial work. In response, we compiled and analysed several food safety evaluation methods, taking into account their nomenclature, size, and validity. We begin by defining food safety and using this discussion as a framework to examine the current landscape of measurement instruments for doing so. We take a close look at the motivations behind these instruments, the areas of food safety evaluated by each measure, the conceptualizations of food safety behind these metrics, and the methods used to verify them. We outline measuring tools that 1) provide national-level estimates of food security, 2) inform global monitoring and early warning systems, 3) examine family food availability and acquisition, and 4) quantify food intake and utilisation. We conclude by providing guidance to direct the selection of relevant food protection indicators, after outlining a number of brilliant size difficulties that may be addressed in future research.

3) In March 2018, G.E.O. Ogutu, W.H.P. Franssen, I. Supit, P. Omondi, and R.W. Hutjes published a research paper titled "Probabilistic Maize Yield Prediction over East Africa using Dynamic Ensemble Seasonal Climate Forecasts" in the journal "Agricultural and Forest Meteorology." The study focuses on utilizing dynamic ensemble seasonal climate forecasts to predict maize yields in East Africa with a probabilistic approach. The paper presents the methodology and results of their research, highlighting the potential of using climate forecasts for crop yield prediction in the region.

We examined whether or if seasonal climate forecasts were helpful for predicting potential outcomes in Japanese Africa. We looked at whether or not the expertise shown by those seasonal forecasts extended to the ability to predict maize yields in those places.Before planting, we used ECMWF device-four ensemble seasonal climate hind casts for the years 1981-2010 at a variety of initiation dates to produce a fifteen-member ensemble seasonal climate hind cast. The World Food Studies (WOFOST) crop model was implemented for water-constrained maize production, and an ensemble of yield forecasts were generated. Focusing on the predominate sowing dates in the north (July), the equatorial vicinity (March–April), and the interior of the south (December), the WATCH Forcing Data ERA-Interim (WFDEI) is used to confirm maize yield estimates against reference yield simulations. When compared to the reliable FAO and country-wide stated facts, these reference yields show strong anomalous correlations; nonetheless, typical reference yield values are lower than those reported in Kenya and Ethiopia, but somewhat better in Tanzania. To evaluate areas of successful probabilistic prediction, we employ the ensemble imply, interannual variability, propose errors, Ranked Probability Skill Score (RPSS), and Relative Operating Curve ability Score (ROC). In most regions, annual yield anomalies may be predicted two months before planting. There is a ten to forty percent difference between the reference and expected yields in terms of interannual variability, with the advantage going to the forecast yield. Reference and expected yield anomaly correlations are generally of good quality, ranging from +0.3 to +0.6. With at least two months' notice, the ROCSS show good pre-season probabilistic prediction of above-average and below-average yields. Our analysis of the data showed that it is possible to anticipate anomalous water-restricted maize yields by combining dynamical seasonal weather predictions with a technique-based crop simulation version of WOFOST.

4) In November 2018, M.E. Holzman, F. Carmona, R. Rivas, and R. Niclòs published a paper titled "Early Assessment of Crop Yield from Remotely Sensed Water Stress and Solar Radiation Data" in the journal "ISPRS Journal of Photogrammetry and Remote Sensing." The study focuses on the use of remotely sensed water stress and solar radiation data to assess crop yield at an early stage. The paper presents the methodology and findings of their research, highlighting the potential of using remote sensing techniques for early crop yield prediction.

Given the large interannual yield fluctuation of rained plants in large agricultural areas, it is crucial to maintain enough soil moisture (SM) for evapotranspiration to provide food security. The photosynthetic rate of vegetated surfaces is affected by the amount of solar radiation (Rs) that reaches the surface. The goal of this study is to evaluate the accuracy of local yield predictions using crop water pressure and Rs remotely sensed information. The TVDI was developed as an indicator of crop water stress and soil moisture content via the use of temperature data and plant water content.

5) In 2016, A. Singh, B. Ganapathysubramanian, A.K. Singh, and S. Sarkar published a paper titled "Machine Learning for High-Throughput Stress Phenotyping in Plants" in the journal "Trends in Plant Science." The paper explores the application of machine learning techniques for high-throughput stress phenotyping in plants. It discusses the potential of using machine learning algorithms to analyze large datasets and extract meaningful phenotypic information related to plant stress responses. The paper provides insights into the advancements and future prospects of using machine learning in plant science research.

There has been a flood of high-resolution images and sensor data of plants as a result of developments in autonomous and high-throughput imaging technologies. To allow information assimilation and characteristic identity for pressure phenol typing, however, system learning (ML) methods must be used to discover patterns and capabilities from this massive corpus of data. (i) identification, (ii) classification, (iii) quantification, and (iv) prediction (ICQP) are four steps of the decision cycle in plant strain phenol typing and plant breeding operations where unique ML algorithms may be applied. Here, we provide a comprehensive evaluation and user-friendly taxonomy of ML equipment, making it possible for the plant network to simply use the most appropriate ML tools and bestpractice guidelines for a wide range of biotic and abiotic pressure trends.

3.EXISTING SYSYEM:

According to Shruti Kulkarni's research paper titled "Predictive Analysis to Improve Crop Yield Using a Neural Network Model," the variation in rice yield between seasons can have detrimental effects on farmers' earnings and livelihoods. Enhancing farmers' ability to predict crop productivity under different climatic conditions can aid in making crucial decisions regarding agronomy and crop selection. In specific districts of Maharashtra State, India, the utilization of neural networks can be employed to forecast rice production and examine the factors that influence rice vegetation growth. The study considered factors such as precipitation, minimum temperature, average temperature, maximum temperature, reference crop evapotranspiration, proximity, manufacturing, and yield for the Kharif season (June to November) from 1998 to 2002. The dataset was processed and transformed using the WEKA software. The author employed Artificial Neural Networks to forecast rice crop yields in Maharashtra, India, and assessed the effectiveness of this approach.

DISADVANTAGES:

- Accuracy is Low.

PROPOSED SYSTEM:

To implement this project, we are using agriculture production dataset and then training above 3 neural networks algorithms on that dataset and building neural network model, we can apply new test data on that model to predict crop yield will be HIGH or LESS. In test data we will have values of location, current year, and agriculture land area and then neural model will predict production.

ADVANTAGES:

- Accuracy is Very high.

UML DIAGRAMS:

Unified Modelling Language is another name for UML. UML, or the Unified Modelling Language, is a standard, general-purpose modelling language used in the area of object-oriented software engineering. The Object Management Group devised and now regulates the trend.

The goal is to make UML the standard language for creating software product-oriented models. Current UML consists mostly of two parts: the Meta-model and the notation. In the future, UML may include or be linked to a new approach or process.In addition to its use in business modelling and other non-software system contexts, the Unified Modelling Language is also widely used for describing, visualising, constructing, and documenting software machine artefacts.

When it comes to the modelling of large and complicated structures, the UML provides a set of high-quality engineering practises that have proven effective.

The UML plays a crucial role in both the software development process and the creation of object-oriented programmes. UML's primary graphical notations are used to describe software project designs.

GOALS:

The Unified Modelling Language was created with the following main objectives in mind:

- Give people an accessible, figurative modelling language to create and share useful models.
- Make it possible to build upon the fundamental ideas by including methods for extension and specialization.
- Don't rely on any one programming language or method of creation.
- A rigorous framework for learning the modelling language should be provided.
- Help the market for OO tools expand.
- Include successful methods.

USE CASE DIAGRAM:

A use case diagram is a type of behavioral diagram within the Unified Modeling Language (UML) framework. It is created based on a use-case analysis and serves the purpose of visually representing the functionalities offered by a system. It showcases actors, their goals (represented as use cases), and any relationships or dependencies between these use cases. The main objective of a use case diagram is to illustrate which system functions are performed for each actor. The roles of the actors involved in the system can also be depicted in the diagram.

Fig 1: Use Case Diagram

CLASS DIAGRAM:

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that depicts the structure of a system by illustrating the classes present in the system, along with their attributes, operations (or methods), and the relationships among these classes. It provides a clear representation of the data encapsulated within each class and how different classes are related to each other within the system. The class diagram helps in understanding the organization of classes and their associations in the system.

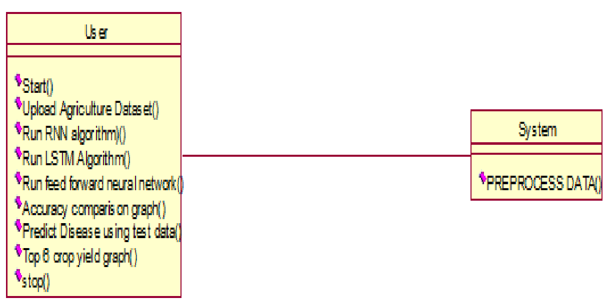

Fig2: Class Diagram

SEQUENCE DIAGRAM:

A sequence diagram depicts the interaction among specific components within a system. Its crucial characteristic is its chronological ordering, meaning that it illustrates the precise sequence of interactions between objects step by step. In a sequence diagram, various objects engage with one another by exchanging messages, which demonstrate the flow of communication. This diagram offers a visual representation of the dynamic relationships and communication patterns between objects, facilitating the analysis and design of system functionality.

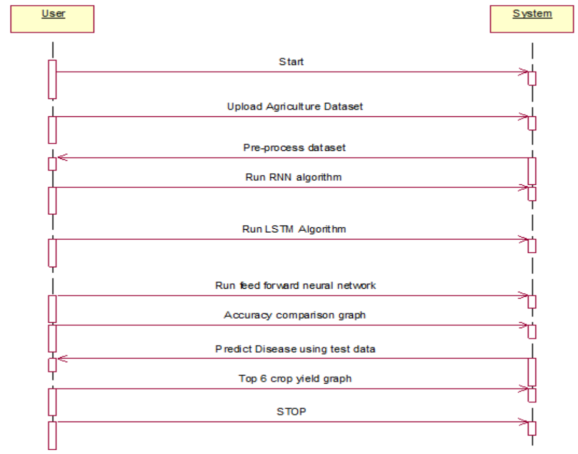

Fig3: Sequence Diagram

7. RESULTS AND DISCUSSIONS

Using RNN, Feed forward, and LSTM Neural Networks, Crop Yield Prediction

In order to carry out this project, we will use data on agricultural production. After training three neural network algorithms on this data and creating a neural network model, we will be able to predict crop yield based on new test data. A neural model will be used to predict production using test data that includes location, current year, and agricultural land area values. Using the test dataset below, we are testing the neural model.

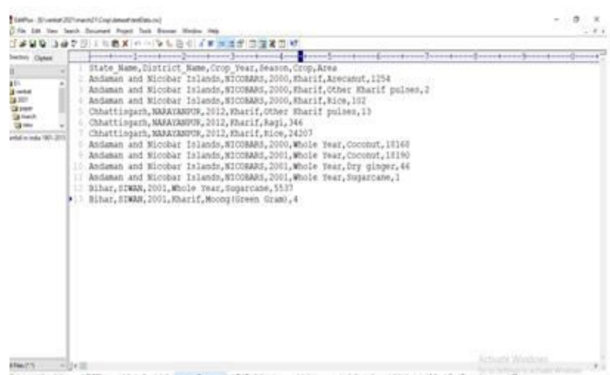

Fig7.1: Dataset

In above test data in last column there is no production values and neural network will predict production will be high or less. In above dataset we have area name, crop name, year and area size.

SCREEN SHOTS

Simply double-click the 'run.bat' file to launch the project.

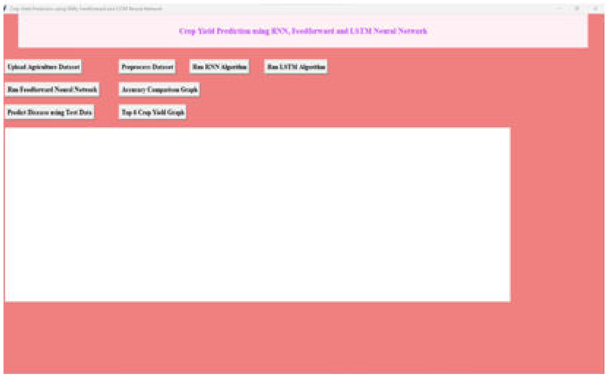

Fig7.2 Upload the Dataset

To upload a dataset, use the 'Upload Agriculture Dataset' button on the aforementioned interface.

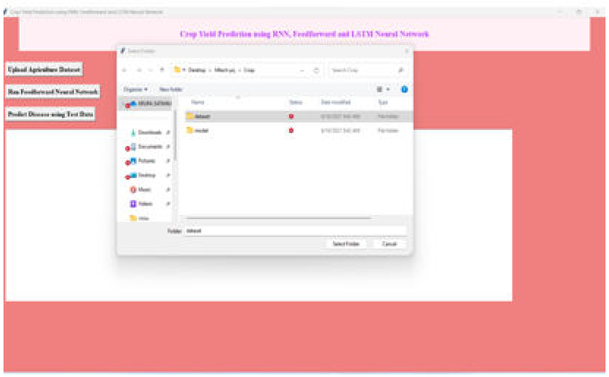

Fig7.3 Upload the dataset file

Below is the result of using the 'Select Folder' button in the previous page to load the 'dataset' folder containing the agricultural and rainfall dataset.

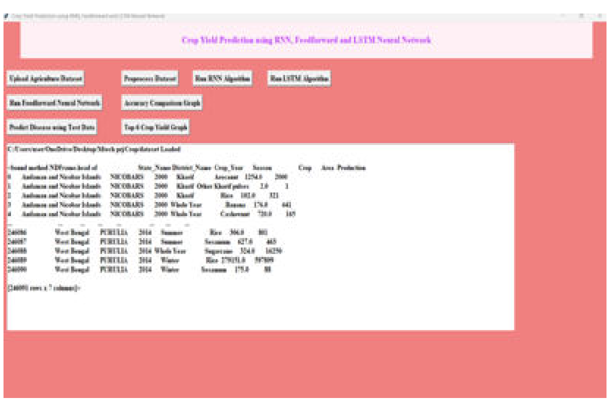

Fig7.4 Pre-process the dataset

The dataset shown in the image above has missing values and string values, which the neural network will not accept. As a result, we must preprocess the dataset in order to replace the missing and string values with numeric data. To access the screen below, click the 'Preprocess Dataset' button.

upload a dataset for agriculture

Prepare the dataset

Use the RNN algorithm

LSTM Algorithm execution

run a neural network with feed forward

Graph of accuracy comparison

Using test results, predict disease

Top 6 crop yields in a graph

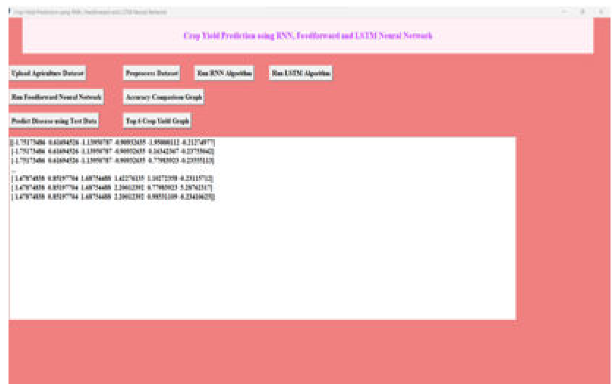

Fig7.5 Run the RNN Algorithm

To create an RNN model using the supplied dataset, choose the 'Run RNN Algorithm' button and see the data being transformed to numerical values.

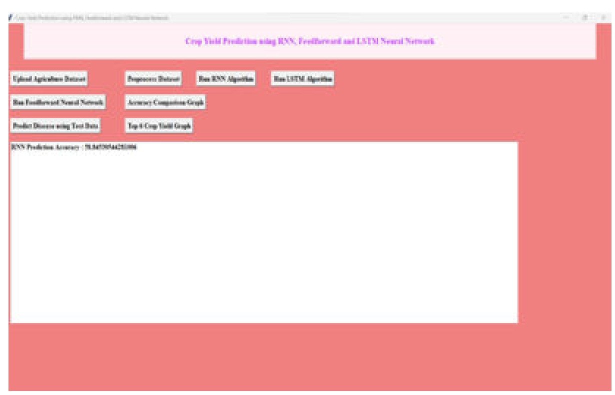

Fig7.6 Run the LSTM Algorithm

To create an LSTM model, choose the 'Run LSTM Algorithm' button on the previous page once the RNN model has been generated with an accuracy of 58%.

Fig7.7 Feed Forward Neural Network Algorithm

To create a feed forward model, choose the 'Run FeedForward Neural Network' option in the previous page, where an LSTM model was just constructed with an accuracy of 78%.

In the preceding window, a feed-forward model was built with an accuracy of 62%; clicking the 'Accuracy Comparison Graph' button yielded the result shown below.

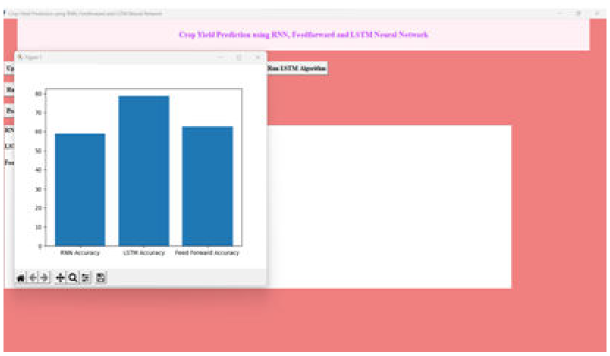

Fig 7.8 Accuracy Comparison Graph

In the above graph, the x-axis indicates the names of the methods and the y-axis reflects their accuracy; among all of the algorithms, LSTM provides the best prediction accuracy. To put this knowledge to use, just choose the 'Predict Disease using Test Data' option and submit your test data for neural network prediction.

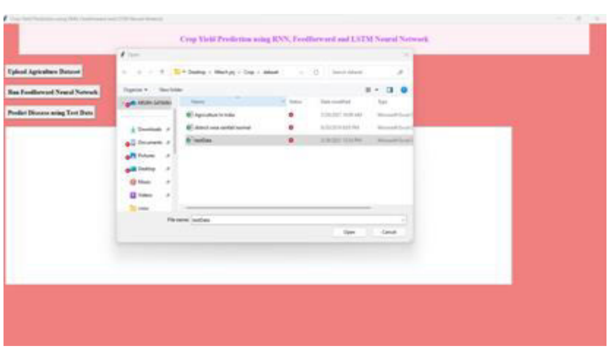

Fig 7.9 Upload The Test Data

Once 'testData.csv' has been uploaded in the aforementioned page and the 'Open' button has been clicked, the output will look like the one shown below.

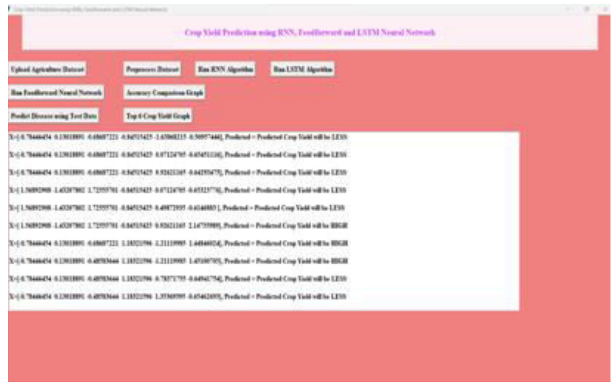

Fig 7.10 Prediction Result

Above, you can see the predicted values (high or low) and the corresponding test values (in numeric format) from the dataset enclosed in square brackets. The output of the neural network will be a forecast based on the agricultural inputs provided. In order to see the following graph, please click the 'Top 6 Crop Yield Graph' button.

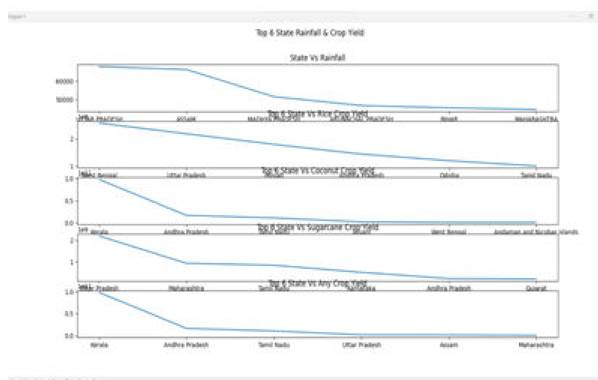

Fig 7.11 Accuracy Graph

The names of the states are shown along the x-axis, while the y-axis details the top six crops grown in each state, including how much rain each receives, rice, coconuts, and sugarcane. The top six crops in each state are shown in the second graph, followed by a comparison of rainfalls in each state to growing conditions for rice, coconut, and sugarcane.

CONCLUSION

Feed Forward Neural Network and Recurrent Neural Network models are used to predict crop production based on relevant crop variables including Minimum Temperature, Maximum Temperature, Relative Humidity, Wind Speed, and Pressure. Root Mean Square Error (RMSE) and Loss were used to assess the performance of the neural network model. RNN is better than FNN for agricultural yield forecasting because it has a lower error rate (as measured by loss of error). Because of this, they are more likely to choose the most lucrative crop for their land. Further research is required to identify the individual diseases that affect the crop and to prescribe a specific pesticide to combat them.

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