1. Introduction:

In the uncertain environment of agriculture, crop yield is one of the most important factors affecting farmers' incomes and food price stability [1]. Supervised machine learning has emerged as a revolutionary force in this field. It is changing our understanding of and ability to predict agricultural prices, providing a hopeful path forward for both farmers and policymakers. It is impossible to exaggerate the importance of machine learning in predicting crop prices. Machine learning algorithms are useful resources for farmers who must contend with the unpredictable nature of weather and changes in the market. We examine enormous databases, considering variables such as past trends, environmental factors, historic yield. Predictions may be made with more accuracy thanks to this detailed study, which offers a clearer knowledge of the complex factors that influence crop prices.

Farmers are better able to make decisions about crop selection, resource allocation, and market timing when they have access to predictive insights. This might protect their revenue and give them the confidence and flexibility to deal with the constantly shifting agricultural terrain. Machine learning has a wider impact on global food security and economic stability than just a single farmer [2]. With the insight gained from machine learning forecasts, policymakers can create focused and successful plans.

Using facts and statistics especially related to the functioning of Indian agriculture, this report examines the Indian market in detail. India presents an intriguing case study for evaluating the accuracy of machine learning in agricultural yield prediction due to its diverse crop landscape and, weather patterns [2][3]. By focusing on Indian affairs, we seek to provide insights that are applicable not only globally but also directly to the npossibilities and problems that farmers, policymakers, and other stakeholders encounter in Indian agriculture. This paper explores the use of linear regression and consequences for agriculture as it dives into the revolutionary role of machine learning in crop yield prediction. By emphasizing machine learning's critical role, we hope to highlight how revolutionary it may be in transforming our understanding of agricultural economics and guaranteeing a more successful and sustainable future for both farmers and the global society.

1.1 Necessity and Applications

Mitigating Risks through Informed Decision-Making: Farmers work in a naturally unpredictable environment where weather, and geopolitical issues are ever-changing. Crop **yield** forecasting becomes essential since it gives farmers the knowledge, they need to make wise decisions. Preventing losses from inefficient use of resources is one of the most important factors. Farmers can obtain an in-depth knowledge of the many aspects impacting crop **yield** by utilizing machine learning algorithms that examine large datasets that include historical **yield data** trends, environmental conditions, and market indicators. With this knowledge, they can plan for changing market conditions, optimize crop choices, allocate resources more effectively, and modify plans to minimize losses [4].

Enhancing Policy Effectiveness for Economic Stability: In addition to influencing individual farmers, agricultural market uncertainty presents difficulties for policymakers concerned with maintaining both food security and economic stability. Crop yield predictions powered by machine learning give policymakers a strong tool to create targeted and efficient plans. Policymakers may predict and handle challenges like production swings and the effects of climate change on agriculture by having precise predictions. Because of this foresight, tailored policies that support a more strong and safe food supply chain may be developed [4]. Policymakers can create measures that reduce the negative effects of market uncertainty, promoting economic stability and strengthening the agricultural sector's overall resilience, by incorporating machine learning insights.

Global Impact on Food Security: Crop yield forecasting is not just important for individual farmers and governments, but also for the larger global community, especially in places like India where crop landscapes are complex, and markets are varied. The ability of machine learning to forecast agricultural yield has a big impact on the security of food worldwide. Making well-informed decisions at the levels of policymakers and farmers promotes a more dependable and sustainable food supply chain. Consequently, this improves the ability of the international community to deal with issues related to yield volatility, disruptions caused by climate change, and market uncertainty [1]. Thus, the revolutionary potential of machine learning in crop yield prediction appears not just as a regional fix but also as an essential element in guaranteeing a prosperous and sustainable future for farmers and societies across the globe.

1.2 Challenges

Complexity of the data: Because agricultural systems are inherently complex, there are non-linear interactions between several components that influence pricing results when it comes to crop yield prediction. One significant obstacle is the possibility that linear models might be unable to adequately represent the complex non-linear patterns found in the data [5]. The predictive ability of linear models may be hampered in the presence of non-linearities since they presume a linear relationship between the input data and the target variable [5][6]. The limits of linear models become apparent in the context of crop yield prediction, when variables specific to each crop, weather patterns.

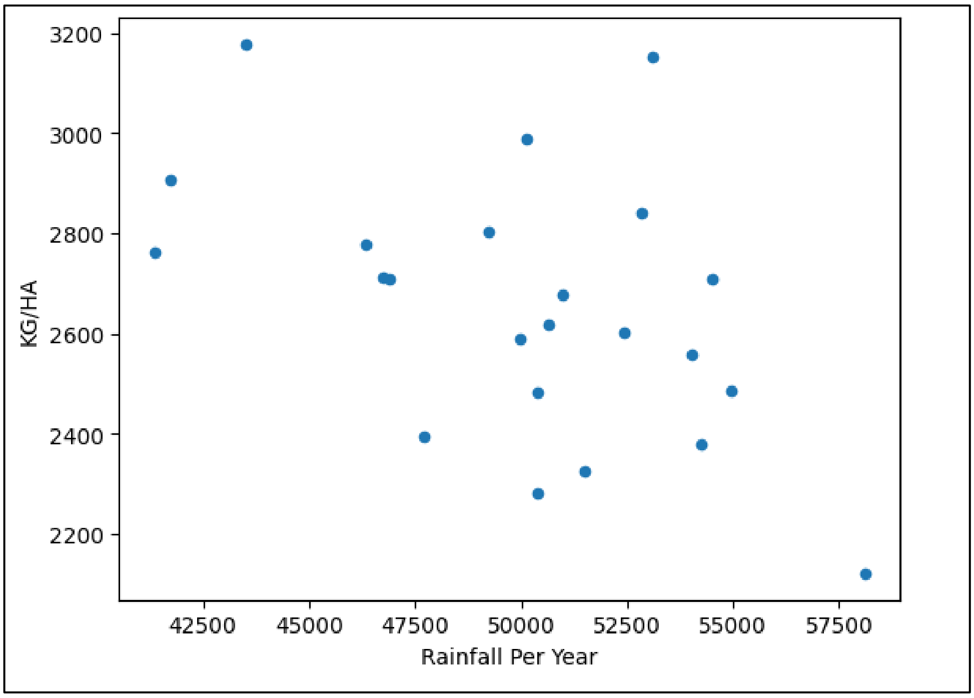


Fig 1: Scatter plot of Annual Rainfall and yield of wheat

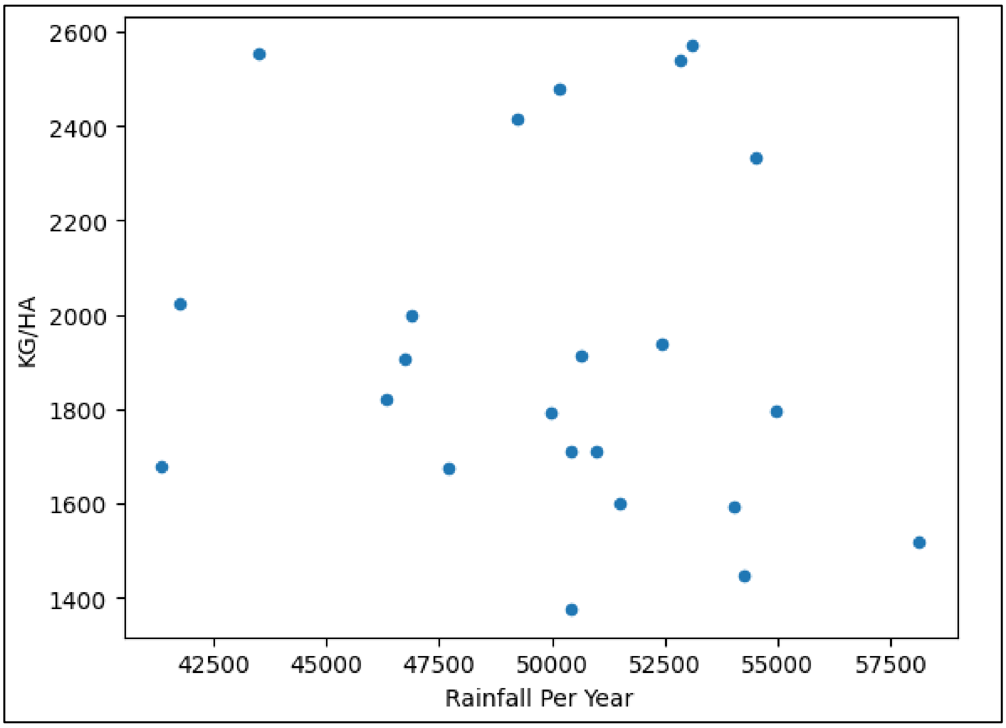


Fig 2: Scatter plot of Annual Rainfall and yield of maize

Low-Quality Data: The possibility of low-quality data presents a major obstacle to machine learning-based crop yield prediction. Incomplete or inaccurate data can result in less-than-ideal model training and, ultimately, inaccurate forecasts. Careful data collecting and preprocessing techniques are essential to overcoming this obstacle [7]. The input data can be made much better by using credible sources like data.gov.in, which is a public dataset managed by the government and offers complete and dependable information on rainfall and crop yield. To remove discrepancies and raise the dataset's general dependability, strict data cleaning and validation procedures must be put in place [7].

Inaccuracy in prediction: Prediction accuracy is crucial to guaranteeing the machine learning model's usefulness in real-world scenarios. Several things can lead to inaccuracy, such as selecting the wrong method or the model's incapacity to accurately represent the intricate relationships present in the data. It is crucial to carefully choose the machine learning algorithm based on the requirements of the prediction task to overcome this difficulty. Previous research has demonstrated the potential of the Decision Tree method and its regressor variation in this application. More accurate predictions can be achieved by carefully evaluating algorithms, like Random Forest Regression. To increase prediction accuracy, regular model evaluation and improvement—including adjusting hyperparameters — are essential.

1.3 Bridging the Gap: Why We Need Machine Learning for Crop Price Prediction

Despite being the foundation of our society, the agriculture industry is yet infamously unstable. There are plenty of unresolved problems for farmers to deal with when trying to forecast crop yield, secure their livelihoods, and make wise decisions. On the other hand, without a thorough grasp of market trends and variations, policymakers find it difficult to create meaningful interventions. This is where ML, or machine learning, shows its potential to be revolutionary. With the use of advanced algorithms and data, machine learning (ML) models can more accurately forecast crop yields, giving farmers and policymakers the confidence to make judgments about agriculture.

1.4 The Farmer's Struggle

Variation in crop yield production is a continual cause of worry for farmers. Anticipating market trends is essential for choosing the correct crop to plant, allocating resources, and making critical choices like harvesting and storing. Unfortunately, in the face of complex factors impacting agricultural yield production, traditional solutions relying on experience or intuition frequently prove insufficient. These factors include:

- **Fluctuations in supply and demand:** Global events, trade policies, and changing consumer preferences can drastically impact market demand for specific crops.
- **Unpredictable weather patterns:** Droughts, floods, and extreme temperatures can significantly affect crop yields, leading to unpredictable price shifts.
- **Volatile production costs:** The cost of fertilizers, pesticides, and labour can fluctuate due to a variety of factors, further complicating the price equation.

1.5 The Policymaker's Dilemma

Policymakers seeking to support farmers and stabilize agricultural markets also face significant challenges. Creating successful interventions such as price floors, trade agreements, and subsidies becomes a guessing game without precise insights of the trends and uncertainties.

- **Ineffective resource distribution**: Weak interventions based merely on intuition might waste important resources and miss the farmers who most need them.
- **Market distortions**: Constructed activities predicated on false premises have the potential to upset the equilibrium of the market, leading to unexpected outcomes for both producers and consumers.

1.6 Filling the Gap: How ML-powered yield forecast can empower.

Here's where your ML model comes in. By harnessing the power of historical data and, weather updates, our model can provide farmers and policymakers with:

- **Precise forecasts:** This model can provide farmers with a better understanding of prospective market trends by examining the complex relationships between many aspects, empowering them to make well-informed decisions regarding planting, harvesting, and resource allocation.
- **Improved risk management:** Farmers may proactively hedge risks by using techniques like futures contracts or insurance, shielding themselves from monetary losses, if they have a better grasp of future price swings.
- **Targeted policy interventions:** With precise price estimates at their disposal, policymakers may create and carry out more successful programs that directly meet the needs of farmers and maintain stable market conditions.
- **Increased market efficiency:** Fairer pricing structures and more seamless market operations result from farmers and buyers making educated decisions based on transparent and trustworthy price insights.

2. Literature Review:

The literature review presents a comprehensive survey of machine learning techniques used to predict crop yields in different geographic and agricultural contexts. Each study focuses on a different combination of input parameters, crop types, and machine learning algorithms, providing unique insights into the predictive modelling process.

Kavita Jhajhariaa, Pratistha Mathura*, Sanchit Jaina, Sukriti Nijhawana conducted research in the Indian state of Rajasthan and covered various crops such as wheat, barley, bajra, and onion. The study uses data on annual rainfall, soil type, and historical crop yields and employs comparative analysis of machine learning algorithms such as random forest, SVM, gradient descent, and LSTM. Their results highlight that SVM is the optimal technique for predicting regional crop yields [8].

Similarly, Martin Kuradusenge 1,* , Eric Hitimana 1, Damien Hanyurwimfura 1, Placide Rukundo 2, Kambombo Mtonga 3, Angelique Mukasine 1, Claudette Uwitonze 1, Jackson Ngabonziza 1 and Angelique Uwamahoro 1 deals with Rwanda's agricultural landscape, with a focus on potato and maize cultivation in Ireland. This study uses data on annual rainfall and crop yields to evaluate the effectiveness of machine learning algorithms such as random forests, SVM, gradient descent, and polynomial regression, and ultimately finds that SVM is the most effective approach. It has been determined that [9].

In contrast, D.Jayanarayana, Dr M. Rudra Kumar Reddy shifts the focus to soil analysis and examines the effects of soil nutrients and type on crop yields without identifying specific plant species. The study uses machine learning techniques such as CNN and "multiple linear regression" and concludes that neural networks, and CNNs in particular, provide better predictive performance than traditional linear regression techniques [10].

R. Murugan, Flaize Sara Thomas, G.GeeAthaShree , S. Glory and A. Shilpa, on the other hand, takes a simpler approach of using annual weather data and past yield records and using a linear regression model to predict crop yields. This simplified and effective methodology demonstrates the potential of optimized predictive models in agricultural forecasting [11].

JavadAnsarifar1*, LizhiWang1 & SotiriosV.Archontoulis2 focuses on rice cultivation in the Indian state of Tamil Nadu and incorporates a comprehensive set of input parameters such as annual rainfall, fertilizer, temperature, and historical yield data. By comparing SVM and linear regression, this study identified SVM as the most suitable method for regional crop yield prediction [12].

Finally, Vinson Joshua1 , A. Selwin Mich Priyadharson1 , Raju Kannadasan2 , Arfat Ahmad Khan3 , Worawat Lawanont3, *, Faizan Ahmed Khan4 , Ateeq Ur Rehman5 and Muhammad Junaid Ali6 investigates crop yield forecasting in Indiana, USA, with a focus on soybean and corn. This study analyses weather patterns, soil quality, and crop yield data and chooses linear regression as the preferred method to predict crop yields in regional agricultural environments [13].

In conclusion, these studies highlight the versatility of machine learning in agricultural forecasting, while highlighting the importance of contextual factors such as geographic location, crop type, and available data inputs.

Using generalized machine learning approaches, researchers can adapt predictive models to specific agricultural environments, ultimately leading to more informed decision-making for farmers and policy makers.

Sr.No-	**Reference**	**Data Set Used**	**Algorithm used**	**Optimal Algorithm**
1	[8]	Rainfall, Soil, yields	SVM, Garadiant Descent, ESTM, Random Forest	SVM with Random Forest
2	[9]	Rainfall, Soil, yields	SVM, Random Forest, Polynomial Regression	SVM with Random Forest
3	[10]	Soil Information, Soil Type, Field, Nutrients	SVM, CNN, Modified Convolutional, Neural Network, Hybrid ANN, ANN, Multiple Linear Regression	Neural Network, Random Forest
4	[11]	Rainfall, Fertilizer, Temperature, Precipitation	BPNN, SVM, GRNN, Multivariable Linear Regression	SVM, ANN
5	[12]	Weather, Soil, Temperature	linear regression	linear regression
6	[13]	Crop Production of past Year, Weather	Linear Regression	Linear Regression

Table 1: Literature Survey Summary

3. Adopted Methodology:

Machine learning be employed to forecast the value of price of a crop for the future. It is a way to teach computers to learn and make decisions without being explicitly programmed for each task. Machines learn from data and patterns rather than from preprogrammed instructions, which enables them to perform better over time [14].

Several crucial phases are included in the machine learning approach, which takes motivation from best practices and the evaluated literature. The emphasis is on applying the optimal algorithm. The "Linear regression" and “Support Vector Machine (SVM)” is employed for regression tasks, which entail making predictions about a continuous output variable. These algorithms were employed to predict the yield of Wheat, Maize and Paddy (rice). Regression challenges concentrate on forecasting a numerical, which aim to predict a certain variable. To generate predictions based on input features, these algorithms construct an approximate relation between the variables.

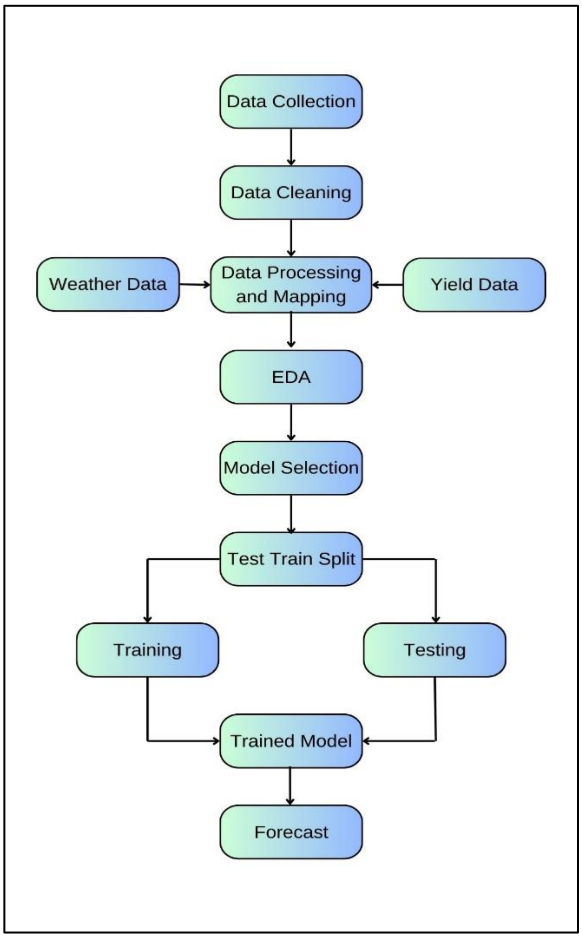


Fig3. Flowchart for methodology

Following are the steps involved in the forecast of the variables.

A. Data Collection:

There are reputed sources for agricultural and environmental data, such as government repositories like www.data.gov.in, agricultural research databases, and meteorological agencies. They have diverse range of datasets including historical crop yield records and rainfall data. The datasets cover a sufficiently long time to capture seasonal variations and trends in crop yields.

B. Data Cleaning:

Finding and removing mistakes, inconsistencies, duplicates, and missing information from data sets is known as data cleaning. A thorough data cleaning addresses issues such as missing values, and inconsistencies across different datasets. Data cleaning tools such as Microsoft Excel or Python libraries like pandas to are used identify and rectify errors and help in data cleaning.

C. Data Processing and Mapping:

The process of gathering, modifying, and altering data to derive meaningful information is known as data processing. Connecting data fields from one source to another is known as data mapping. In data analytics, it's an important step. Functions such as pivot tables and VLOOKUP are used for processing and mapping the data.

D. Exploratory Data Analysis (EDA):

Exploratory data analysis (EDA) is a methodical procedure that aims to summarize the key features of data sets through inspection. Exploratory data analysis gains insights into the underlying patterns and relationships within the dataset.

Seasonal trends, spatial variations, and potential factors influencing crop yield variability through visualizations are explored in this process.

E. Model Selection:

A range of machine learning algorithms are suitable for regression tasks. Linear regression, and Support Vector Machines (SVM) are selected here. That is due to the linear relationship observed during the analysis phase of the data collected.

E.1 Linear Regression

Linear regression analysis is used to predict the value of a variable based on the value of another variable. The variable you want to predict is called the dependent variable. The variable you are using to predict the other variable's value is called the independent variable.

Linear-regression models are relatively simple and provide an easy-to-interpret mathematical formula that can generate predictions. Linear regression can be applied to various areas in business and academic study.

Business and organizational leaders can make better decisions by using linear regression techniques. Organizations collect masses of data, and linear regression helps them use that data to better manage reality — instead of relying on experience and intuition. You can take large amounts of raw data and transform it into actionable information.

Assumptions to be considered for success with linear-regression analysis:

- For each variable: Consider the number of valid cases, mean and standard deviation.
- For each model: Consider regression coefficients, correlation matrix, part and partial correlations, multiple R, R2, adjusted R2, change in R2, standard error of the estimate, analysis-of-variance table, predicted values and residuals. Also, consider 95-percent-confidence intervals for each regression coefficient, variance-covariance matrix, variance inflation factor, tolerance, Durbin-Watson test, distance measures (Mahalanobis, Cook and leverage values), DfBeta, DfFit, prediction intervals and case-wise diagnostic information.
- Plots: Consider scatterplots, partial plots, histograms and normal probability plots.
- Data: Dependent and independent variables should be quantitative. Categorical variables, such as religion, major field of study or region of residence, need to be recoded to binary (dummy) variables or other types of contrast variables.

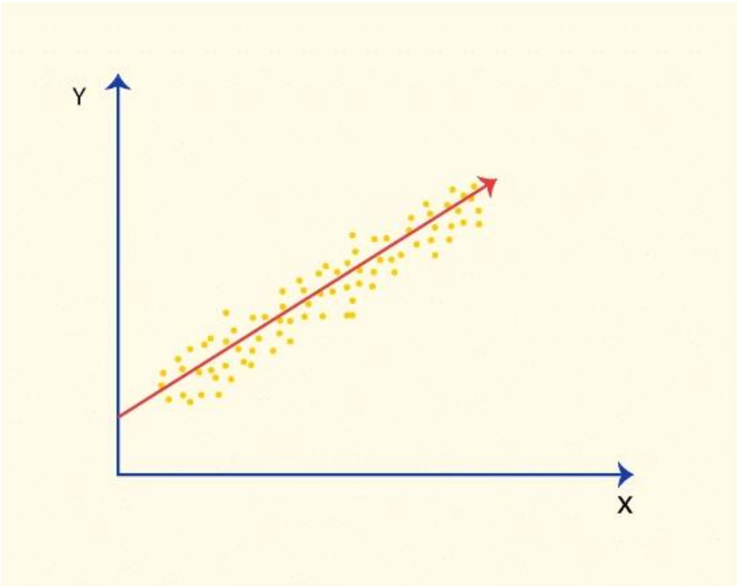


Fig4. Demonstration of Linear Regression

E2. Support Vector Machines

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:

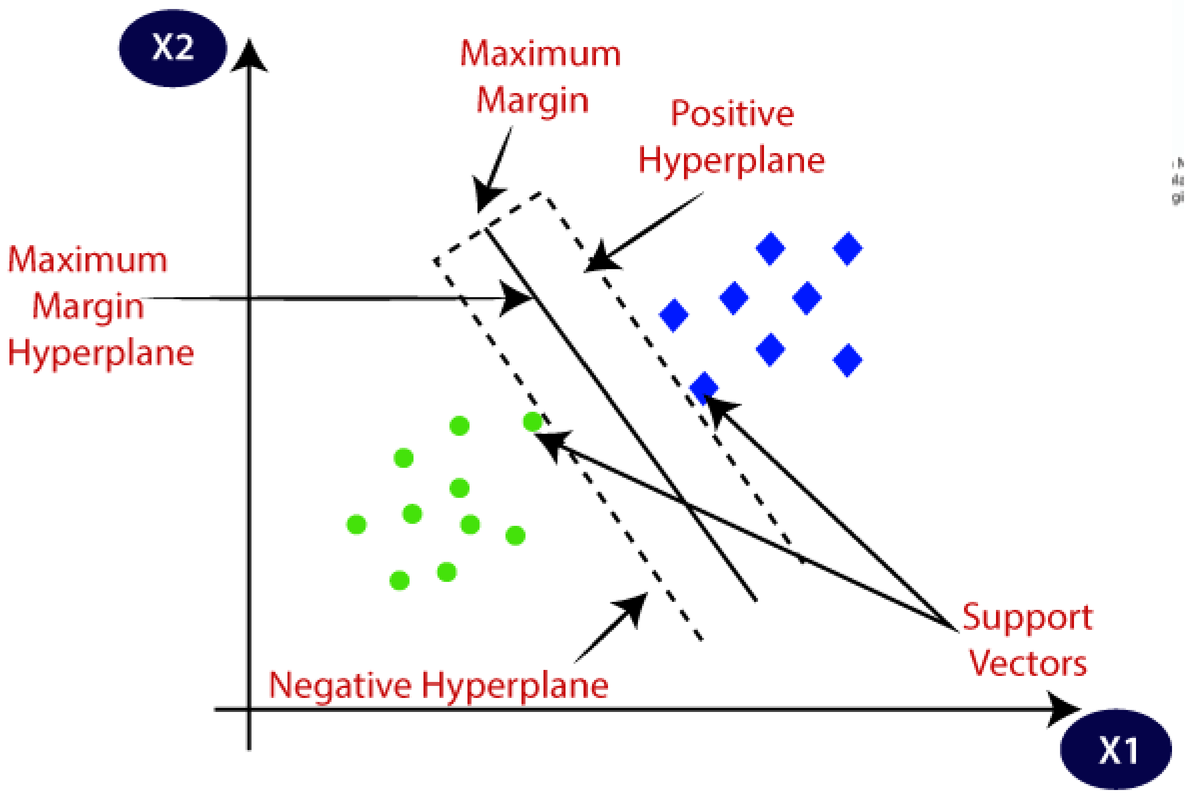


Fig5. Support Vector Machine

SVM regression or Support Vector Regression (SVR) is a machine learning algorithm used for regression analysis. It is different from traditional linear regression methods as it finds a hyperplane that best fits the data points in a continuous space, instead of fitting a line to the data points.

The two main advantages of support vector machines are that: They're accurate in high dimensional spaces; and, they use a subset of training points in the decision function (called support vectors), so it's also memory efficient

F. Data Splitting (Train-Test Split):

To know the accuracy of the machine learning models, it is necessary to test the trained model. In this process, the data is split into two parts. One is used for training the model and the other to know if the model is forecasting the accurate output.

G. Model Training:

The act of providing intended data to a machine learning algorithm to create a model with the best learnt parameters is known as model training. The data that is processed and split from the original dataset is used for the training of the model.

H. Testing:

The trained model is used to forecast crop yields for the dataset which was split for the testing purpose. Its performance is then evaluated through metrics such as accuracy, mean absolute error etc.

The forecasted results are validated against actual observations to gauge the reliability and generalization capability of the model.

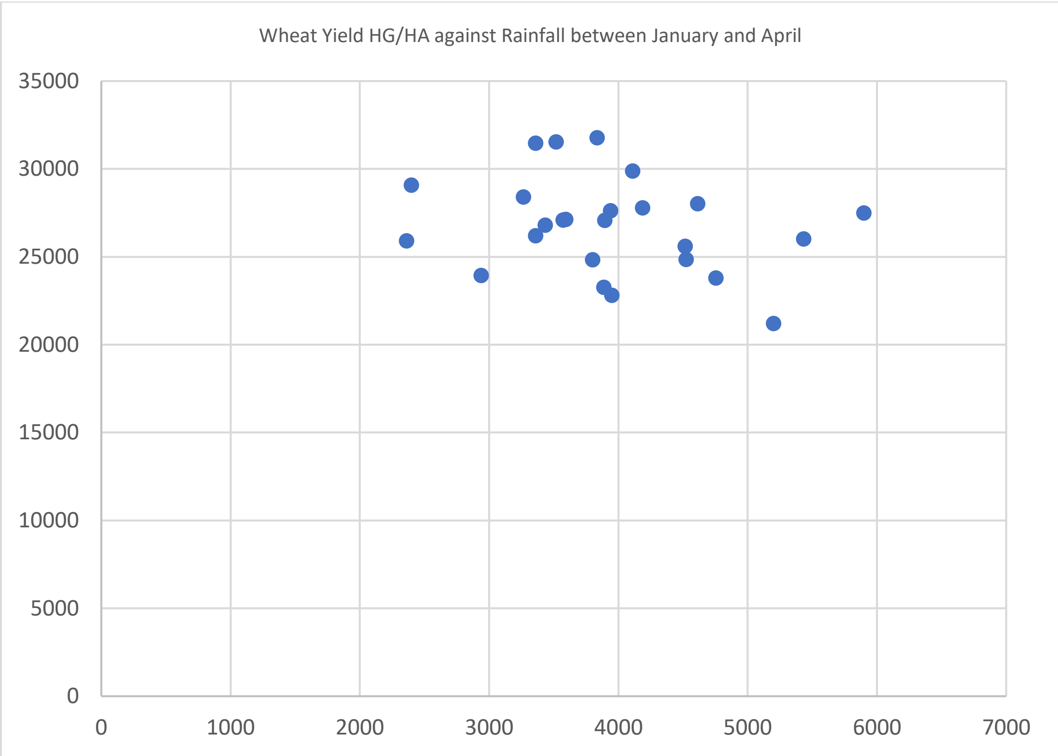
I. Forecast:

Since we have tested the with two different models, we then select the appropriate model for the forecast. We need to feed the model with weather forecasts to predict the yield of the crops.

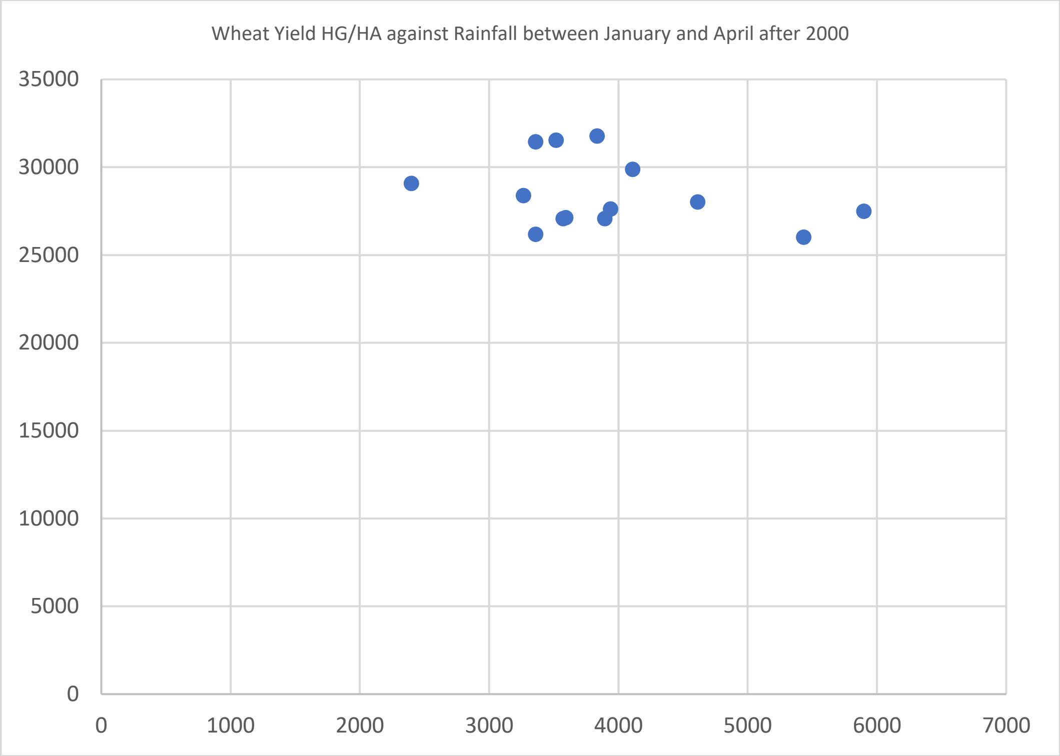
4. Results and discussions:

4.1 Data Patterns

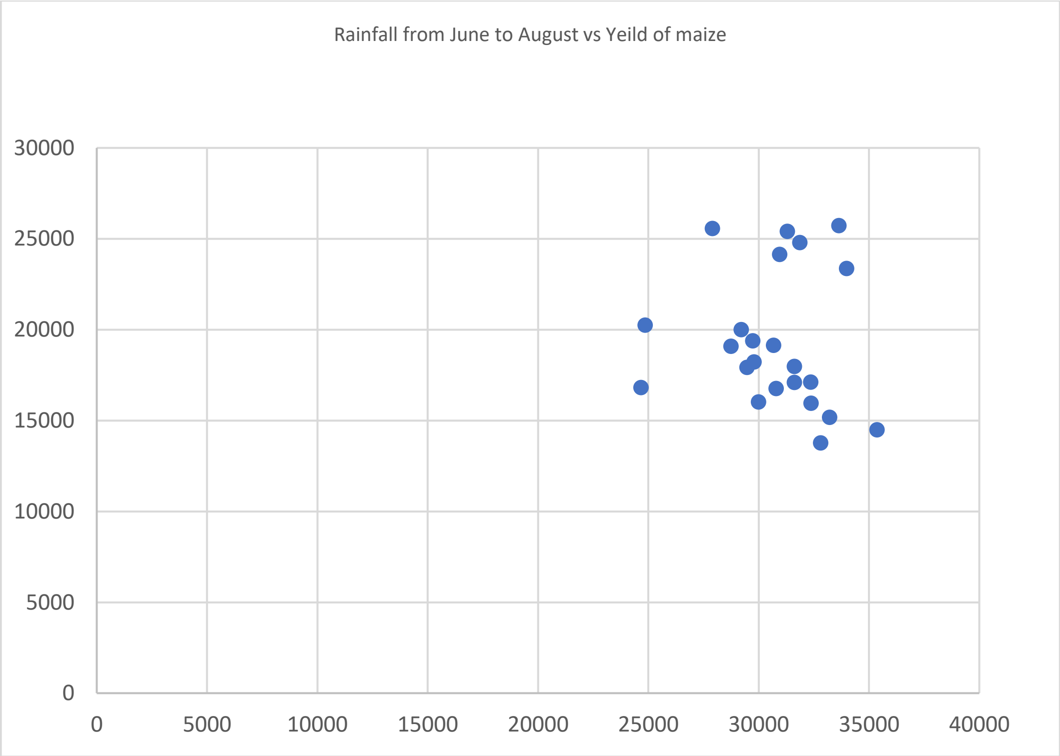
After a thorough analysis of the data, it was found that if we train our model with the data of the rainfall in the season between the time when the crops are sown and when they are harvested, we could get the accurate results. Further, on drilling down through the data, we found that it would be beneficial if we use the of the year after 2000, we could get better results. Here ae some visualizations that prove the same.



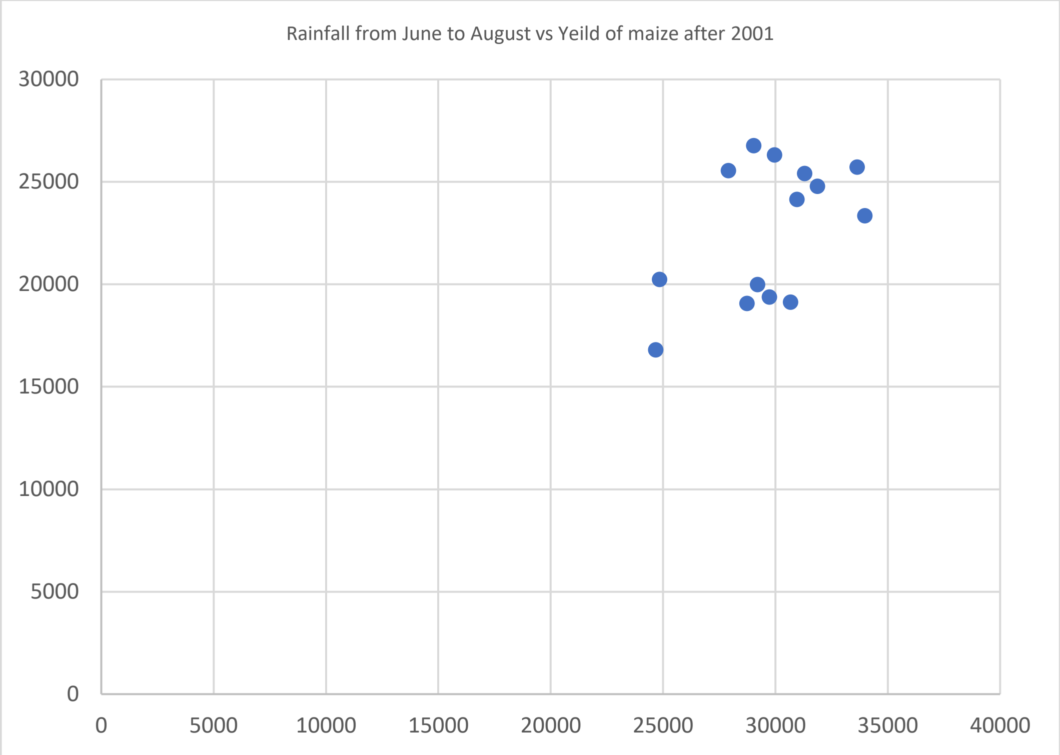
(a)


Wheat Yield HG/HA against Rainfall between January and April after 2000
35000
30000
25000
20000
15000
10000
5000
0
0
1000
2000
3000
4000
5000
6000
7000

(b)


Rainfall from June to August vs Yeild of maize
30000
25000
20000
15000
10000
5000
0
0
5000
10000
15000
20000
25000
30000
35000
40000

(c)


Rainfall from June to August vs Yeild of maize after 2001
30000
25000
20000
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10000
5000
0
0
5000
10000
15000
20000
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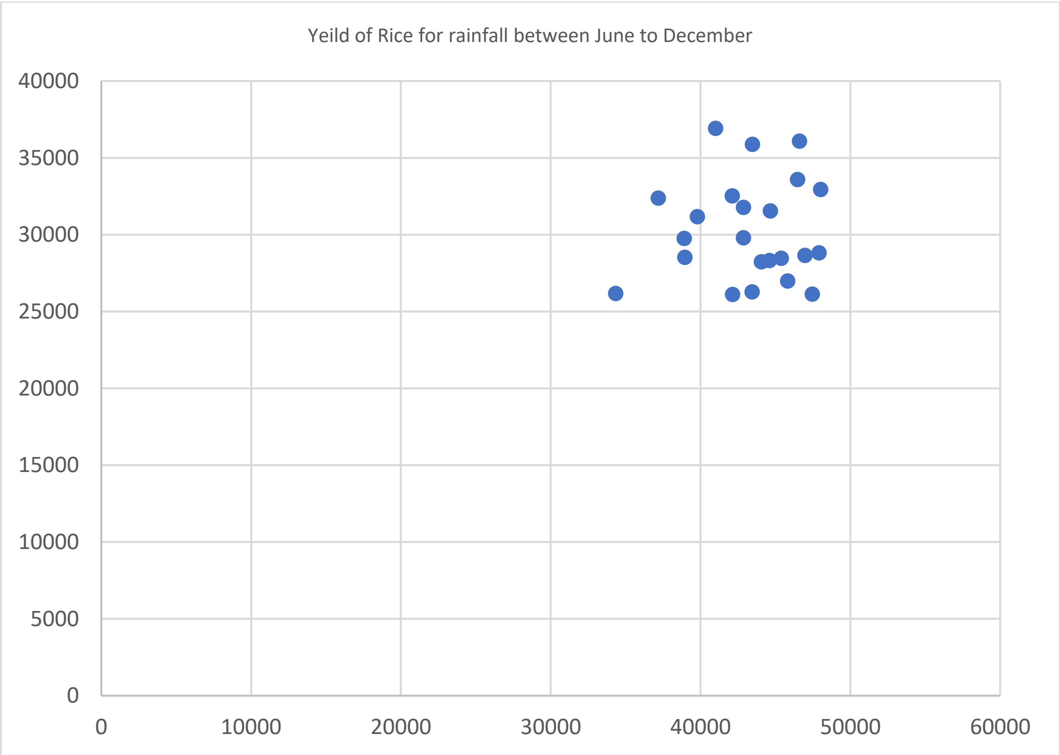
30000
35000
40000

(d)


Yeild of Rice for rainfall between June to December
40000
35000
30000
25000
20000
15000
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40000
50000
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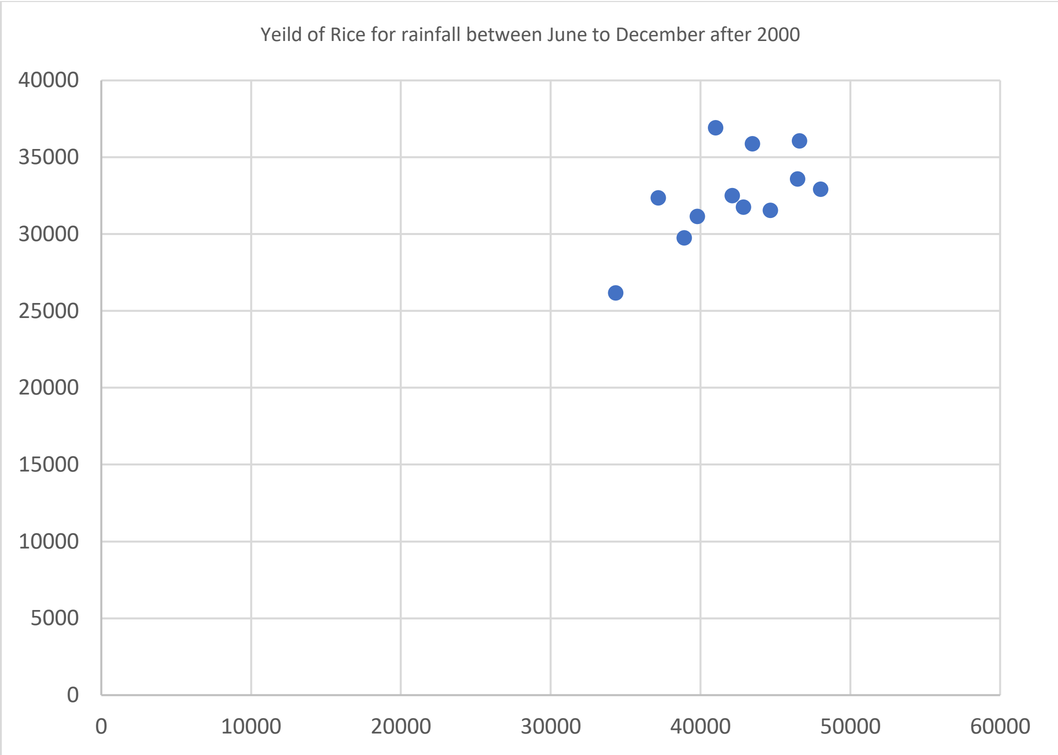
(e)



(f)

Fig5. Scatter plots between season wise rainfall and crops' yield

From the above visuals, it's clearly visible that filtering down the data can get the accurate results. This is because, as per a report India, which had food scarcity until 1950, saw food deficit by 1960 and food sufficiency by 2000. That is due to the change in farming practices and evolution of agriculture in India.

4.2 Comparison of models

Tests were done for the data of these crops with linear regression (LR) and support vector machine (SVM). Following are the results of the tests:

Sr No.	Crop Name	Algorithm	Dataset	Average Accuracy
1	Wheat	LR	Whole dataset	84.3%
2	Wheat	LR	After 2000	90.1%
3	Wheat	SVM	Whole dataset	86.0%
4	Wheat	SVM	After 2000	90.0%
5	Maize	LR	Whole dataset	71.4%
6	Maize	LR	After 2000	70.9%
7	Maize	SVM	Whole dataset	69.0%
8	Maize	SVM	After 2000	77.1%
9	Paddy	LR	Whole dataset	81.9%
10	Paddy	LR	After 2000	88.7%
11	Paddy	SVM	Whole dataset	80.5%
12	Paddy	SVM	After 2000	88.7%

Table2: Results of model testing

5. Conclusion:

The culmination of our exhaustive investigation into the application of machine learning methodologies for forecasting crop production has illuminated profound insights into the efficacy of Linear Regression (LR) and Support Vector Machine (SVM) algorithms. Through meticulous evaluation and rigorous testing, we embarked on a journey to unravel the comparative performance of these algorithms across a spectrum of agricultural parameters, aiming to discern their predictive prowess and identify areas of superiority.

Our exploration unveiled a landscape marked by striking parallels in the predictive capabilities of LR and SVM, traversing through the intricate terrain of agricultural yield prediction. Across diverse crops and varied environmental conditions, both LR and SVM exhibited commendable competence in generating forecasts, capturing the nuanced interplay of factors governing crop growth and yield. This convergence in predictive performance underscores the robustness and versatility of these machine learning techniques in navigating the complexities of agricultural systems.

However, amidst this symphony of similarity, SVM emerged as a luminary, casting its brilliance upon the realm of maize yield prediction. In this pivotal domain, SVM showcased a remarkable edge over LR, transcending the confines of linear relationships to unravel the intricate patterns underlying maize cultivation dynamics. The superior predictive accuracy of SVM in forecasting maize yield underscores its aptitude in discerning non-linear relationships within the dataset, thereby unveiling hidden insights crucial for optimizing maize productivity.

Furthermore, our inquiry into the determinants of predictive efficacy unearthed a pivotal revelation: the cardinal importance of dataset curation in refining the predictive prowess of machine learning models. By meticulously curating the dataset, we circumvented the pitfalls of overfitting, thereby enhancing the robustness and reliability of our predictions. This finding accentuates the paramount significance of judicious dataset selection in mitigating the risk of model bias and augmenting prediction accuracy.

Indeed, the significance of dataset curation transcends mere statistical nuances, resonating deeply with the essence of predictive modeling in agriculture. The intricate tapestry of agrarian systems demands a nuanced understanding of the myriad factors influencing crop production, ranging from soil composition and climatic variations to agronomic practices and socio-economic dynamics. By meticulously curating the dataset to encapsulate these diverse facets, we unlock the latent potential of machine learning algorithms to discern subtle patterns and extract actionable insights for optimizing agricultural productivity.

Thus, the crux of our conclusion reverberates with the imperative for meticulous dataset curation as a cornerstone for augmenting the predictive accuracy and efficacy of LR and SVM algorithms in agricultural yield forecasting. While both LR and SVM exhibit commendable promise in this domain, their true potential can only be realized through judicious dataset selection and refinement. As we navigate the ever-evolving landscape of agricultural innovation, the synergy between advanced machine learning techniques and meticulous dataset curation stands as a beacon of hope, heralding a new era of precision agriculture characterized by sustainable productivity and resilience in the face of global food security challenges.

6. Forecast for 2024

```
print("Predicted wheat yeild",round(wheatModel.predict([[wheatRain]])[0],2))
print("Predicted maize yeild",round(maizeModel.predict([[maizeRain]])[0],2))
print("Predicted paddy crop yeild",round(paddyModel.predict([[riceRain]])[0],2))
```

```
Predicted wheat yeild 28046.32
Predicted maize yeild 23746.56
Predicted paddy crop yeild 32440.93
```

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