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DEVELOPING INNOVATIVE APPROACHES FOR YIELD FORECASTING THROUGH CLIMATE VARIABLES

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ABSTRACT

The agricultural sector plays animportant role in sustaining global food security, making accurate yield prediction an essential component for effective resource allocation, risk management, and policymaking. Traditional methods of yield prediction have relied on historical data, crop modeling, and meteorological parameters. The increasing climate variability and change, there is a growing need to design new methods that harness advanced technologies and incorporate a broader range of climate factors to enhance accuracy and reliability. India's agricultural sector is struggling mightily to increase crop productivity. The crop still depends on monsoon rainfall for more than 60% of its production. The study in this area to forecast crop yield has evolved from innovations in the agricultural field. On the basis of the facts, the yield prediction problem is a significant one that needs to be solved. For this, data mining techniques are the best options. In order to forecast agricultural production for the following year, various data mining approaches are employed and assessed. This study analyses agricultural yield prediction for the chosen region using density-based clustering and multiple linear regression (MLR) techniques.

Keywords: Yield prediction, crop production, Density based clustering

1. INTRODUCTION

Agriculture in Thailand employs 9.37 million people, making it a substantial sector of the economy. Rice, cassava, sugarcane, rubber, and palm are currently Thailand's top five economic crops [1]. Sugarcane is one of the most significant cash crops in Thailand due to its widespread use among farmers and the fact that its price is more lucrative and stable than that of other local goods like rice, cassava, rubber, and palm. Thailand produced 130.91 million metric tonnes of sugarcane worth about USD 176 million in 2019, ranking third in the world behind Brazil and India[2]. In Thailand, sugar mills rather than farmers are in charge of harvesting 63.63% of the sugarcane fields, in accordance with a contract with the farmers. The sugar mill must assess the field in prior to harvest in order to decide how much harvesting equipment, labour, and other resources should be allocated for that field. It has long been difficult to accurately estimate the yield of unharvested sugarcane, and when labour, equipment, and other resources cannot be allocated effectively, this problem has costly effects. Agriculture-related smart technology may offer remedies. Sugarcane yield estimation can be significantly improved by the use of sensor systems, sophisticated data analysis methods, and big data analytics.

The expansion of agricultural lands, variations in regional environmental circumstances, current problems with agriculture, or unfavorable weather conditions. As a result, sugar mills look for reliable and standardized equipment that can more precisely and consistently estimate sugarcane yield. To predict crop yields, many agricultural models have been developed. Environmental data-based models and models that use both environmental data and images can be broadly divided into two kinds. One example of the first kind is a model for predicting sugarcane yield that makes use of an artificial neural network.They developed a model for predicting sugarcane yield that combines the Random Forest algorithm with Crop Simulation. The [3] deep learning-based forecasting model for sugarcane yield. Some models that have already been created employ satellite photos, while others use drone images to incorporate environmental data into their models.

Due to its superior ability to withstand powerful storms compared to other plants, sugarcane has become a favourite among farmers in Kamphaeng Phet. The province's total area under sugarcane cultivation is 0.29 million acres. In the past, studies developed a programme to identify defects in sugarcane that were brought on by bad weather, such as the sugarcane industry that collapses throughout a storm or doesn't grow because of a drought. When compared to professional judgement, the fault recognition model's accuracy is 92.95% based on the analysis of high-resolution, coloured drone photos.

The Wonder cane model, a brand-new sugarcane production forecasting method developed during the study, is based on both an analysis of sugarcane defects and environmental data. When assessing flaws, it's crucial to take into account the distinctive characteristics of each sugarcane field that come from challenging environmental circumstances and affect the final output. The environmental parameters that were found through field studies at sugar mills and through government agencies include rainfall, sugarcane variety, ratoon cut count, planting distance, and soil group. The actual output of previous harvests is another crucial type of information gleaned from sugar mill surveys [4]. A key principle of the Wondercane model is that classification-based data rather than regression-based data is used to estimate expected yield. This is because the classification model can be predicted at the farming size, it requires less time to model than the regression model, and it is simple to incorporate with image analysis data. This model employs a number of feature extraction techniques, such as the Similarities Relationship Method, data mining, the idea of reverse design, and more. The three crucial elements required to create the model are input variables, target outputs, and target output connections. Due to the Wondercane model's properties, yield assessment errors can be successfully reduced and the allocation of resources to sugar mills can be maximized.

1.1 Environmental Factors Affecting Crop Yields

Abiotic and biotic constraints are two categories of environmental limitations that have an impact on crop production. Actually, the effects of climate change brought on by global warming are making these variables more and more visible. Abiotic stresses modify plants' morphology, physiology, biochemistry, and molecular makeup in a number of ways that are detrimental to growth and productivity. Abiotic restrictions include elements like soil composition and weather patterns. Contrarily, biotic variables include infections, weeds, vertebrate pests, and anthropogenic evolution in addition to helpful creatures like pollinators, decomposers, and natural enemies.

1.1.1 Abiotic Constraints

1.1.1.1 Effects of Climatic Conditions on Crops

Among other important indications of climate change, changes in yearly precipitation, average temperature, the worldwide increase in atmospheric CO_2, and sea level oscillations have a substantial impact on crop yields. It is projected that variations in temperature and precipitation would have a significant negative impact on a number of agricultural companies over the following decades. Due to catastrophic weather occurrences that substantially lower food yields as a result of climate change, agriculture is getting increasingly difficult. Because they were primarily chosen for high yield rather than stress resistance, crop plants are typically prone to stresses. Climate change is a result of global warming. It can decrease agricultural productivity directly, indirectly, and socioeconomically by up to 70%. It adversely affects crop output and plant growth.

Regression analysis of historical meteorological data and yield data for food crops over the past 30 years in Nepal showed a mixed trend in precipitation and an increase in temperature ranging from about 0.02-0.07°C each year in various seasons[5]. All crop yields did not substantially correlate with climate variables, however regression analysis revealed associations between wheat yield and winter minimum temperature, maize yield and summer precipitation, and millet yield.

1.1.1.2 Drought

A drought exists when either irrigation, rainfall, or both are not enough to meet the crop's evapotranspiration needs. Variables that affect climate change include variations in water supply as well as water demand for agriculture and other competing industries. Abiotic strains have been observed to adapt to environmental stresses, such as drought brought on by shifting temperature patterns and their effects on the availability of water, the rise in the prevalence of disease and pests, and severe weather on a local to regional scale. The productivity loss of field crops during the crop growth cycle is caused by moisture or drought stress in a proportion of 30–70%.

Stomatal closure may result from an accumulation of abscisic acid in guard cells brought on by drought stress [6]. Drought not only has an impact on metabolism, but it can also stunt plant development or even kill it. The flowering stage of a plant is the most vulnerable to the impacts of drought, which vary depending on the stage of development.

1.1.1.3 Heat Stress

Heat stress can be described as an increase in temperature that surpasses a particular threshold and lasts for an extended period of time and permanently inhibits plant growth and development. By the year 2050, the Intergovernmental Panel on Climate Change projected a temperature increase of 3–4°. Agricultural phenology, reproductive biology, blooming timing, pollinator populations, photosynthetic efficiency, and seed germination rates are all impacted by high temperature regimes brought on by climate change[7]. The reproductive growth stage's increased temperature brought on by heat stress stops pollen grains from expanding, which results in insufficient pollen discharge from the anther during dehiscence. Heat stress has a detrimental effect on plant development, notably the production and function of reproductive organs. Furthermore, unpredicted disease epidemics could spread across much of the world as a result of irregular temperature patterns. Maize yields decrease by 1.0-1.7% each day when temperatures exceed 30°C, making up to 40% of the entire yield loss in wheat.

1.1.1.4 Cold Stress

When plants are exposed to chilling stress between 0 and 15 degrees Celsius in agriculture, there are significant losses. Many tropical or subtropical crops suffer damage from non-freezing low temperatures, and some can perish. These crops may exhibit inadequate germination, stunted seedlings, chlorosis or retarded growth, limited leaf expansion and wilting, and necrosis, to name a few symptoms. Plants generally modify their pattern of protein synthesis and gene expression when subjected to cold temperatures. Plants from temperate climes, as opposed to tropical and subtropical crops, are generally thought to be more accepting of chilling, and they can increase their freeze resistance by being acclimated to cold temperatures.

1.1.1.5 Soil Properties

The main processes that lead to the creation of soils, which make up the topmost layer of the earth's crust, are material mobility, humus growth, and rock weathering. They differ from one another in terms of their external design, level of manufacture, and country of origin. Soil fertility refers to a soil's capacity to offer the nutrients required for a crop's optimum growth. Soil fertility is among the key elements in crop growth [8]. It can support crop production based on the complete range of its chemical, physical, and biological properties. Because it is a substantial source of the macro- and micronutrients needed for plant growth, soil fertility is important for soil productivity. While toxicities are brought on by an excess and decreased agricultural production, plant shortages are produced by a lack of certain nutrients in the soil.

A number of variables can be used to evaluate the fertility of a soil. The most useful indicator for increasing sustainable land use management and achieving a high agricultural production was found to be the soil fertility index. Some croplands have experienced human-induced soil deterioration in numerous parts of the world, which has led to low yield production per area of harvested crops. The degradation of agricultural areas brought on by humans affects about 40% of them. A loss in soil health, land degradation, and serious environmental issues result from intensive agricultural production that is characterized by excessive fertilizer and chemical use [9]. It is crucial to remember that the loss of soil fertility often occurs over a period of years.

1.2 Biotic Factors Affecting Crop Yields

1.2.1 Diseases and Pests

Numerous microbes, including bacteria, fungus, and viruses, are capable of infecting plants. Numerous above-ground and soil-borne insect pests can affect crop productivity. The production of plants and the fertility of the soil are usually negatively impacted by climatic variations, which promotes the spread of diseases. Plants are unable to produce adequate biomass, seeds, or yield because there are fewer resources available to them.

Pathogens and pests may migrate due to the climate, moving from one place to another. In order to cope with new biotic stresses, the locally adapted crop genotypes must. Resistance to illnesses secondary infections might result from a plant's interactions with microbes or molecular patterns connected to bacteria. This involves the production and movement of several low-molecular-weight plant metabolites, which are easier to comprehend in monocotyledonous plants than in dicotyledonous plants. Cereal crops are an example of one such monocotyledonous plant. New illnesses and pests could appear as a result of climate change and unpredictability, and existing ones could become more destructive.

Climate change has resulted in the emergence of new species of pest and disease that are now ineffectively controlled. For instance, maize lethal necrosis is one of the most destructive diseases that affects maize in several regions of Eastern and Central Africa. It results from the interaction of the sugarcane mosaic virus and the maize chlorotic mottle virus. Infestations can affect crop production in farmers' fields by 30% to 100%, depending on when they occur [11]. A few species of non-persistent aphids, beetles, rootworms, thrips, stem borers, contaminated soil, contaminated seeds, and any tools or materials used in the contaminated field are all MLN carriers. The Russian Wheat Aphid is another invasive insect that affects wheat, barley, and other cereal crops. It is common in areas where grains are grown, such as those in Africa, Asia, Europe, the Middle East, North and South America, and most recently, Australasia [12]. Plants that have been infected display withering, stunting, longitudinal leaf lines that are pale, yellow, and purple, imprisoned awns, rolled leaves, and heads that do not bloom. These insects are incredibly resistant to bad weather. By as much as 80% and 100%, respectively, RWA decreased wheat and barley yields. The fundamental issue with the RWA is that more and more biotopes are developing a tolerance to the available pesticides. Some biotopes also get beyond some crop kinds' resilience. Additionally, it has been found that increased atmospheric carbon dioxide has an impact on various biotopes effectiveness. As a result, they continue to represent a threat to crop yield.

2. LITERATURE REVIEW

Pradawet et. al. (2023) [13]analyzed thatMaize production in Thailand is increasingly suffering from drought periods along the cropping season. To avoid yield loss, this necessitates the development of quick and precise technologies to identify crop water stress. The goal of this study was to boost thermal imaging's precision for spotting water stress in maize and predicting production. In Phitsanulok, Thailand, the experiment was conducted in both controlled and wild environments. Five different treatments were utilized, including (T1) a fully irrigated treatment in which 100% of the crop's water needs were managed; (T2) an early stress treatment in which 50% of the crop's water needs were managed from 20 days after sowing until anthesis, after which rewatering was used; (T3) a sustained deficit treatment, where 50% of the crop's water needs were managed from 20 DAS until harvest; (T4) a late stress treatment, where 100% of the crop's water needs were managed up until anthesis and 50% of them from anthesis. Crop growth, soil moisture, and canopy temperature were observed every five days. Early water stress significantly reduced maize output and growth under controlled conditions.

Muthukumaran et. al. (2023) [14]investigated that the process of producing food, which takes up almost one-third of the earth's area, depends heavily on agriculture. Paddy seeds are used to grow rice, which is a dependable food that is consumed by approximately half of all people worldwide. They must ensure food security due to the worrisome rate of population growth, and the country must make the required steps to boost the production of food grains. The goal of the study is to increase paddy yield by using evolutionary computation techniques to forecast the variables that affect paddy growth. To forecast the output of paddy, the majority of specialists examined historical records of the weather. There isn't many research on how paddy farming is affected on a daily basis by meteorological factors including wind direction and speed, relative humidity, and Instant Wind Speed. Real-time meteorological data was gathered, and regular time series were employed, to evaluate the effects of the weather from the day of paddy sowing to the last day of paddy harvest. To anticipate the elements that farmers should take into consideration in order to maximize rice production in cultivation, a resilient optimized artificial neural network approach including genetic algorithms and multi objective particle swarm optimization algorithms was developed.

Cedric et. al. (2022) [15]analyzed thatGlobal agricultural production, in particular, is of increasing concern to the major international organizations in charge of nutrition. A number of inhabited places, most notably Africa, are experiencing food insecurity as a result of the increased worldwide demand for food brought on by historical population expansion. The major international organizations in charge of nutrition are becoming increasingly concerned about agricultural productivity in both Africa and the world. The World Food Programme claims that the recent high population growth, particularly in Africa, has improved world food security. A sophisticated set of tools is also required for farmers and agricultural decision-makers to make prompt judgements that will affect the quality of agricultural produce. The issue of climate change has received a lot of attention internationally in recent decades. Climate change has been shown to affect agricultural output standards.In this study, they suggest a machine learning-based prediction system to anticipate the yield of six crops at the national level in the region of West African countries during the course of the year, including rice, maize, cassava, seed cotton, yams, and bananas. They included climate data, meteorological information, agricultural yields, and chemical data to help decision-makers and farmers forecast the annual crop yields in their country.

Elavarasan et. al. (2020) [16]conducted that predicting crop yield based on the environmental, soil, water and crop parameters has been a potential study. It is widely employed to extract essential crop properties for deep learning prediction models. These approaches may be able to solve the yield prediction problem, but they suffer from the following limitations: Because there are no direct unpredictable or linear mappings between the raw data and crop output, the effectiveness of the models is heavily reliant on the quality of the retrieved attributes. Deep reinforcement learning is used to address and motivate the aforementioned issues. By combining the intelligence of deep learning and reinforcement learning, deep reinforcement learning offers a comprehensive yield prediction framework that can convert the raw data to the crop prediction values. The study provides a Deep Recurrent Q-Network model, a deep learning method for recurrent neural networks built upon the Q-Learning reinforcement learning algorithm, in order to forecast crop yield.

Cai et. al. (2019) [17]investigated thatWheat is the most important staple crop grown in Australia, and Australia is one of the top wheats exporting countries globally. For regional and global food security, accurate and on-time Australian wheat crop forecasts are essential. Using either climate data, satellite data, or a mix of the two, previous research have created empirical models to predict agricultural productivity. Even though combining climate and satellite data increases the accuracy of yield forecast using empirical techniques, it is still unknown how different data sources contribute. Additionally, it is unclear how the performance of the regression-based methods compares to those of different machine-learning-based methods in terms of yield prediction, and further research is required. To forecast wheat yield at the statistical division level across Australia from 2000 to 2014, this study combined data from multiple sources. The higher values of climate factors are sustained throughout the entire season, not just at certain specific times, as shown by our empirical modelling study, which goes beyond what the satellite data have already supplied for yield prediction.

Khaki et. al. (2019) [18]conducted thatCrop yield is a highly complex determined by multiple factors such as genotype, environment, and their interactions. In order to disclose this functional relationship between yield and various interaction elements, rich datasets and potent algorithms are both required for accurate yield prediction. The genotype and yielding capacities of 2,267 maize hybrids planted in 2,247 locations between 2008 and 2016 were tracked, and participants in the 2018 Syngenta Crop Challenge were required to predict the yield performance in 2017 based on a range of huge datasets. Innovative modelling and resolution strategies were used by some of the winning teams to construct a deep neural network strategy. The validation dataset using forecasted weather data demonstrated that our model had a greater level of prediction accuracy, with a root-mean-square-error of 12% of the average yield and 50% of the standard deviation. The RMSE would be reduced to 11% of the average yield and 46% of the standard deviation with excellent meteorological data.

Choudhury et. al. (2014) [19]examined thatClimate and other environmental changes in the developing world and the African continent has become a major threat to their agricultural economy. Traditional insurance for managing financial risk is ineffective in underdeveloped countries because of high transaction costs, unfavourable selection, information asymmetry, insufficient distribution, and other problems. A promising strategy for lowering financial risk for smallholder farmers in developing nations like Ghana is area-based index insurance. But in determining how much one should charge for this insurance policy, the yield is important. Due to the importance of crop yield forecasting, the objective of this study is to employ a variety of forecasting approaches for evaluating agricultural output estimates in Ghana. Ghana's economy relies heavily on crop production predictions, which provides information to decision-makers. By applying different ARMA, Damped-Trend Linear Exponential Smoothing, Simple Exponential Smoothing, and Double Exponential Smoothing models to each district, they may compare yield estimations. In this study, the ARMA models beat the smoothing methods as more accurate time-series models for predicting agricultural yield.

Barnwal et. al. (2010) [20]investigated thatthis study examines the effects of temperature and precipitation on the mean and 7 variance of seasonal rice yield in Andhra Pradesh, India, over a period of 33 years (1969-2002). According to the first technique, the cropping season has a significant impact on an increase in precipitation, whereas an increase in temperature, inter-annual variance in temperature, and rainfall all have a negative impact on the average crop yield. Along with average temperatures, rainfall, and their related inter-annual variance, it is expected that agricultural productivity would likewise experience an increase in inter-annual variability. Second, the quantile regression shows that there are considerable differences in the sensitivity of rice yield to changes in the climate among the quantiles of yield distribution. Climate change's negative consequences are thought to be getting worse, especially for agricultural yields at lower quantiles. According to some research, the effects of climate change on various agroclimatic zones appear to vary as well. These results demonstrate the need for more site-specific adaptation policies to handle variability and a thorough policy framework encompassing downside risk to increase the resilience of the food security system.

Table 1: Comparison of review table

Reference	Objective	Methods	Key Findings
Pradawet et. al. (2023) [13]	Identify crop water stress in maize, production	Thermal imaging, controlled and natural env., canopy temp., crop growth, soil moisture	Early water stress severely impacts maize growth, in controlled conditions.
Muthukumaran et. al. (2023) [14]	Increase paddy yield using meteorological data	Real-time meteorological data, optimized ANN, genetic algorithms, and particle swarm opt	Real-time weather data aids paddy yield forecast with anoptimized ANN.
Cedric et. al. (2022) [15]	Predict yield of six crops in West African countries	Machine learning, climate, weather, agricultural and chemical data	A machine learning-based prediction system for six crops at the country-level.
Elavarasan et. al. (2020) [16]	Predict crop yield using deep learning and reinforcement learning	Deep Recurrent Q-Network model	Deep reinforcement learning improves crop yield prediction.
Cai et. al. (2019) [17]	Forecast wheat yield in Australia	Combined climate and satellite data	Climate data provides valuable info for yield prediction in Australia.
Khaki et. al. (2019) [18]	Predict maize yield using datasets	Deep neural network strategy	High prediction accuracy using deep neural network model.
Choudhury et. al.	Assess agricultural yield	ARMA, Exponential	ARMA models outperform

(2014) [19]	in Ghana	Smoothing models	smoothing techniques for yield forecasting in Ghana.
Barnwal et. al. (2010) [20]	Study climate impacts on rice yield in Andhra Pradesh	Statistical analysis	Climate change negatively impacts rice yield, especially in lower quantiles

3. METHODOLOGY

The statistical technique of multiple linear regression and the data mining technique of density-based clustering were both applied in this study's estimation of agricultural yield analysis.

3.1 Multiple Linear Regression

A multiple regression model is one with numerous predictor variables. You can visualize the linear relationship between a dependent variable and a number of independent factors using multiple linear regression. Sometimes the dependent variable is referred to as the predictor, whilst sometimes the independent variables are referred to as the predictors. It's probable that the least squares-based Multiple Linear Regression method is the one that climatologists choose to use when building models to reconstruct climatic variables from tree ring data. The Multiple Linear Regression approach is used to provide this crop yield projection model. The year, rainfall, sowing area, yield, and fertilizers are the seven predictors.

3.2 Density-Based Clustering Technique

The core concept of density-based clustering methods is that, at a given unit distance, each point in a cluster must be surrounded by at least a particular minimal number of other points. There should be a particular level of density in the area. However, the premise of this idea is that the clusters have spherical or uniform shapes. These techniques arrange the objects in accordance with particular objective functions for density. The quantity of data objects in a given region is the standard definition of density. In these methods, a particular cluster keeps expanding so long as there are more objects in the area than a certain threshold. This is thought to differ from the concept of partitioning algorithms that use iterative point relocation to produce a specific number of clusters.

4. RESULT

In this study, analysis of the region-specific agricultural yield data is conducted using both the multiple linear regression technique and the density-based clustering technique. All of Andhra Pradesh's districts were included in the experiments using these models, but only the East Godavari district was used in the evaluation procedure. For a sample of data collected over a 40-year period, the exact value and the associated estimated value using the Multiple Linear Regression approach are displayed in Table 2.

The estimated results using Multiple Linear Regression technique which are ranging between -14% and +13% for 40 years interval.

Table 2: Exact production and estimated values using Multiple Linear Regression technique

Observation Year	Production (Exact)	Production (Estimation)	Percentage of Difference
2011	683422	592460	13
2012	579851	566050	2
2013	551115	579432	-5
2014	762452	722638	4
2015	743614	742751	0
2016	348726	399062	-14
2017	547715	551541	-1
2018	715472	691068	3
2019	716608	697226	3
2020	616567	633494	-3

In Table 3, crop yield prediction estimates for an approximation of six clusters of sample data for the East Godavari District are given using a density-based clustering technique. The results, which roughly correspond to six clusters and range between -13% and +8% when utilizing density-based clustering.

Table 3: Exact production and Estimated values using Density-based clustering technique

Observation Year	Production (Exact)	Production (Estimation)	Percentage of Difference
2011	683422	666010	3
2012	579851	651103	12
2013	551115	566972	-3
2014	762452	703913	8
2015	743614	737897	1
2016	348726	392771	-13
2017	547715	534708	2
2018	715472	791588	-11
2019	716608	676320	6
2020	616567	695574	-13

Table 4 and Figure 1 below present a regression technique for a 40-year interval and a density-based clustering technique for an estimate of six clusters for the East Godavari District.

Table 4: Comparison between Exact production and estimated values using Multiple linear Regression technique and Density-based clustering technique

Observation Year	Production (Exact)	Production (Estimation)	
		Multiple linear Regression Technique	Density based Clustering technique
2011	683422	592460	666010
2012	579851	566050	651103
2013	551115	579432	566972
2014	762452	722638	703913
2015	743614	742751	737897
2016	348726	399062	392771
2017	547715	551541	534708
2018	715472	691068	791588
2019	716608	697226	676320
2020	616567	633494	695574

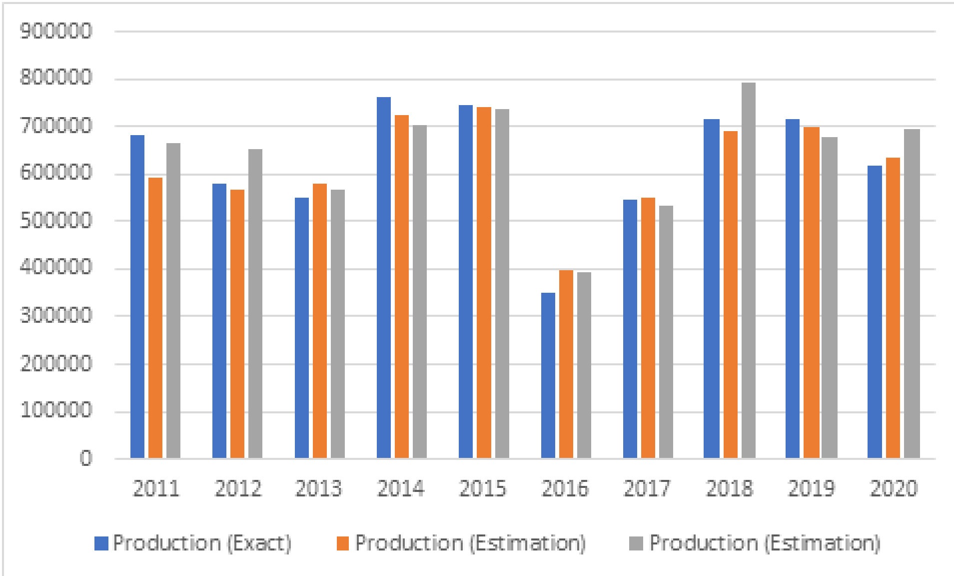

Figure 1: Comparison between Multiple Linear Regression technique and Density based Clustering technique

CONCLUSION

The statistical model's Multiple Linear Regression method is used. Specifically, the density-based clustering technique from data mining was used to verify and analyses the results. In this process, the outcomes of two strategies were contrasted in terms of the particular region. A similar procedure was put into place for all of the state's districts with the goal of improving and validating yield prediction that is useful to Andhra Pradesh farmers for the forecast of a crop. A comparison of the crop production prediction with the whole set of currently available data can be done in the following study, which will also focus on appropriate strategies for boosting the effectiveness of the suggested strategy.For sustainable agriculture in the face of climate change, advanced yield prediction techniques that take climate considerations into account must be developed and put into use. These techniques could increase agricultural resilience, increase food security, encourage sustainability, and encourage cooperation between many stakeholders. To be widely used and successful in the future, these inventions will need to be adopted widely and the accompanying problems must be solved.

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