# PROJECT REPORT

On

**MALL CUSTOMER SEGMENTATION**

Submitted in the Partial Fulfilment of the Requirement for the Award of

# BACHELOR OF TECHNOLOGY

**In**

## ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING (2025)

By

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**Affiliated to**

**Dr. APJ ABDUL KALAM TECHNICAL UNIVERSITY, UTTAR PRADESH, LUCKNOW**



**ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING**

**SHRI RAMSWAROOP MEMORIAL COLLEGE OF ENGINEERING AND MANAGEMENT**

## CERTIFICATE

Certified that the project entitled **“Mall Customer Segmentation”** submitted by **Tanuja Pathak [2101221640054]** and **Vanshika Tiwari [2101221640058]** in the partial fulfilment of the requirements for the award of degree of Bachelor of Technology (Information Technology) of Dr APJ Abdul Kalam Technical University (Uttar Pradesh, Lucknow), is a record of student’s own work carried under our supervision and guidance. The project report embodies results of original work and studies carried out by students and the contents do not form the basis for the award of any other degree to the candidate or to anybody else.

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**INFORMATION TECHNOLOGY**

**SHRI RAMSWAROOP MEMORIAL COLLEGE OF ENGINEERING AND MANAGEMENT**

## DECLARATION

We hereby declare that the project entitled **“Mall Customer Segmentation”** submitted by us in the partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (Artificial Intelligence and Machine Learning) of Dr. APJ Abdul Kalam Technical University (Uttar Pradesh, Lucknow), is record of our own work carried under the supervision and guidance of **Er. Anuj Singh**, Assistant Professor.

To the best of our knowledge this project has not been submitted to Dr. APJ Abdul Kalam Technical University (Uttar Pradesh, Lucknow) or any other University or Institute for the award of any degree.

**Tanuja Pathak Vanshika Tiwari**

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**Tanuja Pathak Vanshika Tiwari(2101221640054) (2101221640058)**

## PREFACE

In the ever-evolving landscape of retail, understanding customer behavior has become a cornerstone of strategic decision-making. Mall customer segmentation, a data-driven approach to categorizing shoppers based on shared characteristics, offers invaluable insights into diverse consumer preferences and habits. As competition intensifies and consumer expectations grow, businesses must move beyond one-size-fits-all strategies. Segmentation empowers retailers to tailor marketing efforts, optimize resource allocation, and enhance customer experiences, ensuring they meet the nuanced demands of different demographic and behavioral groups. This analytical pursuit not only bridges the gap between data and action but also fosters a customer-centric culture essential for sustained growth.

The objective of this project is to unravel the hidden patterns within mall customer data, transforming raw information into actionable intelligence. By leveraging advanced clustering techniques, such as *K-means* or *hierarchical clustering*, we aim to identify distinct customer segments that reflect variations in spending habits, age, income, and lifestyle. These segments can reveal high-value customers, budget-conscious shoppers, or trend-driven individuals, enabling businesses to craft personalized promotions, loyalty programs, and inventory plans. Beyond commercial benefits, this analysis underscores the ethical imperative of respecting consumer privacy while harnessing data to drive mutually beneficial outcomes.

Ultimately, mall customer segmentation transcends mere technical exercise; it represents a strategic tool for fostering meaningful customer relationships. By translating clusters into personas, stakeholders can empathize with their audience, anticipate needs, and innovate proactively. In an era where data is abundant but insights are scarce, this project exemplifies how analytics can transform retail landscapes, driving profitability while enriching customer satisfaction. As we delve into this exploration, we invite readers to appreciate the synergy between data science and human-centric commerce—a synergy that promises to redefine the future of retail.

This preface aims to set the stage for the detailed project report that follows, outlining the structure of our documentation. The project is divided into several key chapters, each dedicated to a specific aspect of the project:

#### Chapter 1: Introduction

#### This chapter introduces the Mall Customer Segmentation project, outlining its purpose and relevance in targeted marketing.

#### Chapter 2: Literature Review

We explore existing research and techniques used in customer segmentation, highlighting their benefits and limitations.

**Chapter 3: Proposed Methodology**

#### This section describes the data collection, preprocessing, clustering algorithms, and tools used for segmentation.

#### Chapter 4: Results

#### We present the segmented customer groups and insights derived from the clustering analysis.

#### Chapter 5: Conclusion

#### This chapter summarizes the key findings and overall impact of customer segmentation on business strategy.

#### Chapter 6: Future Scope

We propose future improvements such as real-time segmentation, deeper personalization, and integration with recommendation systems.

## ABSTRACT

In the competitive retail landscape, understanding customer diversity is critical for strategic decision-making. This project focuses on mall customer segmentation, employing data analytics and machine learning techniques to categorize shoppers into distinct groups based on demographics, spending habits, and behavioral traits. By analyzing datasets encompassing variables such as age, gender, income, and purchase frequency, the study aims to uncover latent patterns that drive consumer behavior. The insights derived from this segmentation enable businesses to personalize marketing strategies, optimize resource allocation, and enhance customer satisfaction, fostering long-term loyalty in an increasingly dynamic market.

The methodology integrates exploratory data analysis (EDA) with unsupervised learning algorithms, primarily *K-means* and *hierarchical clustering*, to identify homogeneous customer clusters. Data preprocessing steps, including normalization, outlier detection, and dimensionality reduction via *Principal Component Analysis (PCA)*, ensure robust model performance. Visualization tools such as heatmaps, scatter plots, and silhouette analysis aid in interpreting cluster validity and coherence. The project also addresses challenges like feature selection bias and algorithmic scalability, ensuring the model’s practicality for real-world retail applications.

Key findings reveal four primary customer segments: *high-income luxury seekers*, *budget-conscious shoppers*, *experience-driven millennials*, and *low-engagement occasional buyers*. Each segment exhibits unique characteristics—for instance, luxury seekers demonstrate high annual income and frequent purchases, while budget-conscious customers prioritize discounts and seasonal sales. These distinctions underscore the need for tailored marketing approaches, such as VIP loyalty programs for high-spenders and targeted promotions for price-sensitive groups, to maximize engagement and revenue.

The project emphasizes the ethical implications of data usage, advocating for transparency in collecting and analyzing customer information. While segmentation enhances business outcomes, it also raises concerns about privacy and algorithmic fairness. Strategies to anonymize data and mitigate bias in clustering outcomes are discussed, aligning technical practices with regulatory standards like GDPR. This balance ensures that customer trust remains intact while leveraging analytics for competitive advantage.

Practical applications of the study extend beyond marketing to inventory management, store layout optimization, and customer service enhancements. For example, identifying experience-driven millennials could prompt investments in interactive in-store technologies, while insights into low-engagement buyers might inform re-engagement campaigns. The project demonstrates how data-driven segmentation bridges the gap between theoretical analytics and actionable business strategies, offering a roadmap for retailers to thrive in a data-centric.

In conclusion, mall customer segmentation serves as a transformative tool for modern retail, converting raw data into strategic assets. By aligning machine learning outputs with consumer psychology and business goals, this project highlights the symbiotic relationship between technology and human-centric commerce. Future research could explore real-time clustering using streaming data or integrate psychographic variables for deeper behavioral insights, further refining the precision and impact of customer segmentation models.

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# CHAPTER-1

# INTRODUCTION

The retail industry thrives on understanding customer behavior, and mall customer segmentation has emerged as a cornerstone strategy to decode the complexities of consumer preferences in a rapidly evolving market. By categorizing shoppers into distinct groups based on shared traits, businesses can tailor experiences, optimize marketing efforts, and foster loyalty. This project aims to leverage data analytics in converting raw customer data into actionable information to meet the urgent need for specificity in an age when generic strategies do not quite cut it.

The core aim of this study is to identify and examine mall customer patterns using variables like age, income, gender, and buying behavior to develop useful segments. Retailers are unable to manage resources efficiently when confronted with heterogeneous consumer needs, resulting in lost opportunities and weakened marketing effect. This research seeks to fill that gap by using sophisticated clustering methods to reveal underlying behavioral patterns, allowing companies to focus on high-value customers and reactivate dormant ones.

One of the most important issues in contemporary retail is the inefficacy of blanket marketing efforts, which do not speak to particular demographics or psychographics. Without granular segmentation, companies stand to alienate niche markets, overinvest in low-return activities, or misestimate nascent trends. This project addresses these issues by introducing a data-driven approach that substitutes guesswork with empirical data, guaranteeing strategies are aligned with the subtle needs of various customer cohorts.

The goals of the present work are three: first, to identify the important variables that have the greatest impact on purchasing behavior in mall environments; second, to use unsupervised machine learning techniques such as K-means and DBSCAN to segment customers into meaningful clusters; and third, to map these clusters into executable business strategies. By connecting analytical insights to real-world applications, the research aims to equip retailers with tools for hyper-personalized interaction.

The project's scope is carefully narrowed to orderly, quantitative information from mall shoppers' profiles in the form of transactional histories, demographic characteristics, and visit frequencies. Focusing narrowly achieves clarity and practicality, avoiding distraction from non-core variables like macroeconomic environments or competitor action. Excluding qualitative data like customer comments or psychographic interviews is an accepted limitation, making complementary studies required in the future.

Ethical issues are at the heart of this research, specifically in terms of data privacy and algorithmic fairness. The analysis is based on anonymized datasets to safeguard individual identities, and stringent checks are applied to reduce bias in clustering results. By following regulations such as GDPR, the project highlights the need to balance innovation with consumer confidence, providing transparency in how data is gathered, processed, and used.

Methodologically, the research starts with exploratory data analysis (EDA) to determine outliers, correlations, and distributions in the data. Methods such as PCA (Principal Component Analysis) lower dimensionality, making the clustering easier while maintaining essential information. Visualization tools such as heatmaps and silhouette plots then confirm the consistency of segments so that results are both statistically significant and understandable to non-technical stakeholders.

The issue of overgeneralization is countered by focusing on the specificity of every cluster. For example, affluent luxury seekers might have high frequency buying and loyalty to brands, whereas value shoppers focus on promotions and holiday selling. Identifying these differences enables retailers to develop specific promotions, loyalty clubs, and stock plans to meet individual tastes, optimizing ROI and customer satisfaction.

The other essential element of the project is scalability. The system is made to adjust to changing data sizes and shifting consumer patterns, making it useful for both small boutique malls and big retail chains. Through clustering processes being automated and real-time updates in data, the model stays useful in changing markets, providing a long-term solution for strategic planning that is sustainable.

The research's real-world ramifications reach beyond marketing. For instance, customer segment insights can be used to optimize store layouts, staffing levels, and event design. Discovering low-participation clusters may trigger re-engagement efforts, and discovering high-spending segments may call for investments in high-end services or targeted offers, having a knock-on effect on operational effectiveness.

To conclude, this project sets customer segmentation at the mall as a revolutionary tool for contemporary retail, combining data science and consumer psychology to spur actionable results. By balancing technical rigor with business insight, it sets the benchmark for retailers to ride out competitive environments with dexterity and vision. Future studies could build out into real-time clustering or incorporate psychographic variables, further enhancing the accuracy and effectiveness of segmentation models.

Finally, the foreword highlights the mutually beneficial interplay between analytics and human-driven commerce. In a time when information is plentiful but understanding is lacking, this book is the best example of how disciplined analysis can light the way to customer-driven innovation, keeping malls alive, dynamic destinations in the age of the Internet.

### Research background:

The idea of customer segmentation has been a pillar of marketing planning for decades, based on the understanding that customers are not one entity but rather a mosaic of varying tastes, habits, and requirements. Retailers in the past used primitive groupings—age, sex, or income levels—to adapt their products. The digital era and the increased use of data analytics have elevated segmentation to an advanced, evidence-based science. In the context of malls, where foot traffic and purchasing patterns are influenced by a blend of socio-economic, psychological, and situational factors, segmentation has become indispensable for optimizing tenant mix, promotional campaigns, and customer experiences. Early studies, such as those by Kotler (1994), emphasized segmentation’s role in enhancing market efficiency, but contemporary research underscores its criticality in an era of hyper-personalization and omni channel retail.

The advance of machine learning and big data technologies has otherwise continued to transform segmentation methodologies. Methods such as clustering algorithms (K-means, DBSCAN) and dimensionality reduction (PCA) now allow retailers to handle enormous datasets, revealing underlying patterns that standard approaches would possibly not see. Empirical research by Wedel and Kamakura (2000) established contemporary segmentation on a solid foundation of quantitative techniques combined with theory from behavioral science, and more recent empirical studies (e.g., Gupta et al., 2019) emphasize the importance of real-time analytics in dynamic profiling of customers. Mall managers, especially, stand to gain from these developments since spatial and temporal information—dwell time, sequences of store visits, and seasonal peaks in spending—can be combined to forecast trends and make strategic resource allocation.

Even with advances in technology, there are challenges in obtaining precise and actionable segmentation. A study by Dolnicar (2003) criticizes excessive use of purely demographic or transaction-based data, asserting that psychographic factors—like lifestyle, values, or social influence—are equally important but underrepresented. This deficiency is especially felt in mall environments, in which emotional drivers such as ambiance, social interactions, or perception toward a brand heavily influence behavior. In addition, research by Smith et al. (2020) has found that segmentation models often do not consider cultural or regional differences and hence may produce biased results in multicultural markets. Such flaws point to a demand for combining quantitative measurement with qualitative analysis to achieve segments that are statistically sound yet also contextually significant.

Ethical issues have now come to the forefront of segmentation studies. With increasing public pressure regarding data privacy, researchers such as Martin and Murphy (2017) recommend data transparency practices and fairness of algorithms in processing sensitive attributes such as income or ethnicity. The General Data Protection Regulation of the European Union has further amplified this debate, pushing retailers to reconcile personalization with privacy. In mall environments, where data capture ranges from in-store sensors to loyalty cards and mobile apps, ethical segmentation involves anonymization, consent, and stringent bias testing. Recent case studies (e.g., Lee & Kim, 2022) illustrate that ignoring these paradigms may cause consumer mistrust and consequently undermine the very value segmentation aims to provide.

The scholarly and operational imperatives in mall customer segmentation merge in its ability to promote sustainability and inclusiveness. Jones et al. (2021) research shows how segmentation can help detect environmentally friendly consumer segments, allowing malls to market green brands or minimize waste through targeted programs. Likewise, segmentation models that identify low-income or marginalized consumers promote inclusive retail spaces, which are consistent with international Sustainable Development Goals (SDGs). As malls become hybrid environments merging commerce, entertainment, and community involvement, segmentation studies need to go beyond profit-oriented measures to reflect on the wider societal implications. This research project draws upon these foundations to advance segmentation methodologies and integrate ethical and inclusive considerations into their core.

### Problem Statement:

In the intensely competitive retail market, malls and retailers find it more and more difficult to effectively connect with diverse customer bases because they rely on outdated, generalized marketing techniques. Old methods tend to segment customers based on superficial factors such as age or income, without considering sophisticated behavioral patterns, preferences, and contextual variables that influence buying decisions. The rigid one-size-fits-all approach results in ineffectual utilization of resources, lost chances of cultivating high-margin segments, lowered customer satisfaction levels, and dilution of profitability and brand fidelity in an environment where personalization is a value driver.

Overlaid is the inefficient exploitation of advanced analytical capabilities given the vast amount of customer information emanating from customer loyalty schemes, transaction histories, and digital transactions. Most malls do not possess the technical capabilities or know-how to integrate and analyze such data at a holistic level, resulting in piecemeal insights. For example, frequencies-only clusters will miss out on key psychographic motivators such as lifestyle or emotional drivers, while neglecting consideration of real-time changing behavior (e.g., seasonality, new preferences) makes static segment models defunct. This disconnect between data access and actionable insights suppresses innovation, and companies are not well-positioned to respond to changing market conditions.

Adding to the complexity are ethical and operational issues, such as privacy, bias in algorithms, and resistance to change within organizations. Retailers stand to lose customers if segmentation activities are seen as intrusive and discriminatory, especially where sensitive traits such as ethnicity or socioeconomic status are abused. Moreover, even clearly defined segments rarely make it to the level of effective strategies because of siloed departments, rigid legacy systems, or the absence of cross-functional collaboration. Unless these complex barriers are addressed, malls cannot maximize the potential of customer segmentation, and inefficiencies continue while their capacity to succeed in a more data-driven retail environment is hampered.

### Objectives of the Project:

* + - Define the most effective variables (e.g., age, income, spending behavior, frequency of visit) that identify disparate customer segments within mall settings based on exploratory data analysis and statistically validated measurement.
    - Utilize unsupervised machine learning techniques (K-means, hierarchical clustering) to segment customers into meaningful, actionable groups, maximizing the validity of clusters using metrics such as silhouette scores and elbow method analysis.
    - Translate Insights into Business Strategies: Translate segmentation findings into targeted marketing strategies, individualized promotions, and operational suggestions (e.g., inventory control, loyalty schemes) to drive customer interaction and ROI.
    - Guarantee Ethical and Inclusive Practices: Integrate privacy-protecting methods (data anonymization, bias reduction) and inclusivity verification to guarantee segmentation complies with ethical practices and serves varied demographic segments.

### Scope of the Project:

#### The scope of the study is aimed at solving issues in mall customer segmentation and developing retail strategies through a systematic, multidimensional method. It includes the following main areas:

#### Data Collection and Ethical Practices: The research will investigate data collection methodologies (e.g., loyalty programs, IoT sensors, transaction records) and analyze ethical concerns, such as privacy compliance (GDPR, CCPA) and anonymization strategies. This entails reviewing potential data sourcing biases and transparency in customer information storage and usage.

#### Segmentation Methodologies:

#### The project will explore state-of-the-art machine learning methods (K-means, hierarchical clustering, DBSCAN\*) to cluster customers into significant groups. It will test the validity of the clusters using measures such as silhouette scores and gap statistics, and overcome challenges like feature selection, dimensionality reduction (e.g., PCA), and interpretability of results.

#### Technology Integration and Real-Time Analytics: The research will delve into the application of AI-based solutions (such as CRM, mobile applications, predictive analytics tools) to provide real-time customer insight. This also involves considering the viability of dynamic segmentation models that change behavior, seasonal, or new emerging patterns of shopping.

#### Operational and Marketing Applications: The scope encompasses examining how segmentation intelligence can streamline mall operations, including tenant mix, staffing schedule, and inventory management. It will also suggest customized marketing strategies (e.g., personalized promotion, reward loyalty) to drive customer retention and conversion rates.

#### Customer Experience Optimization: The research will determine the effect of segmentation in enhancing in-mall experiences, such as spatial configuration changes, event organization, and digital interaction (e.g., app notifications). It will measure the effect of hyper-personalization on metrics such as dwell time and repeat visits.

#### Socioeconomic and Inclusivity Implications: The project will take into account the wider social consequences of segmentation, such that models do not marginalize low-income or minority segments. It will suggest methodologies for inclusive retailing practice, for instance, fair access to discounts or services, and will examine how segmentation supports wider aims such as sustainability or community involvement.

#### The scope is broad, spanning technical, operational, and ethical considerations to translate raw data into actionable customer-focused strategies. By impacting these interrelated factors, the research hopes to promote retail innovation, support fair practice, and improve the competitiveness of malls in the digital-first economy.

# CHAPTER-2

**LITERATURE REVIEW**

#### Customer segmentation, with its roots in marketing theory, became a strategic instrument to tackle diverse consumer needs. Early literature by Smith (1956) presented the idea of "product differentiation," stating that markets can be segmented by demographic or geographic characteristics. Kotler (1967) took this further, promoting segmentation as a way to maximize targeting effectiveness. In mall settings, Bonoma and Shapiro (1983) highlighted the significance of behavioral variables (e.g., loyalty, purchase frequency) to calibrate retail strategies. These early works anchored on segmentation as the link between market diversity and business scalability.

1. **Evolution of Segmentation Techniques**

Traditional segmentation was highly dependent on demographic (age, income) and geographic information, but critics such as Wedel and Kamakura (2000) pointed out the disadvantages of failing to account for nuances in behavior. The advent of transactional databases during the 1990s facilitated RFM (Recency, Frequency, Monetary) analysis, which became prevalent following the work of Hughes (1994), classifying customers according to expenditure patterns. Such models, though, were handicapped by dynamic markets, where fixed clusters proved unable to keep pace with contemporaneous behavioral changes.

1. **Psychographic and Behavioral Segmentation**

Psychographic segmentation, incorporating lifestyle and personality characteristics, was popularized by Plummer's (1974) VALS typology. For mall environments, Solomon's (2016) studies identified emotional drivers (e.g., entertainment, social status) as strong drivers of in-store activity. Behavioral segmentation, employing dwell time and path tracking (through IoT sensors), was examined by Hui et al. (2013), showing its potential for use in streamlining store configuration and promotions.

1. **Machine Learning Revolution**

The emergence of machine learning turned the segmentation heuristic-to-algorithmic. K-means clustering as used in grouping customers by Jain et al. (1999) was pioneering, and the sensitivity to starting centroids was objected to by Punj and Stewart (1983). Hierarchical clustering as seen in Xu and Wunsch's (2005) application did provide dendrogram-based conclusions, but was scaly to do with massive sets. Comparative investigations (e.g., Hsu & Lin, 2016) found that DBSCAN performs well when seeking non-spherical clusters within sparsely indexed transactional databases.

1. **High-Dimensional Data Challenges**

The emergence of machine learning turned the segmentation heuristic-to-algorithmic. K-means clustering as used in grouping customers by Jain et al. (1999) was pioneering, and the sensitivity to starting centroids was objected to by Punj and Stewart (1983). Hierarchical clustering as seen in Xu and Wunsch's (2005) application did provide dendrogram-based conclusions, but was scaly to do with massive sets. Comparative investigations (e.g., Hsu & Lin, 2016) found that DBSCAN performs well when seeking non-spherical clusters within sparsely indexed transactional databases.

1. **Ethical and Privacy Concerns**

With increasing data intensity of segmentation, ethical challenges arose. Martin and Murphy (2017) emphasized threats of algorithmic bias, especially when clustering involves sensitive characteristics (e.g., ethnicity). GDPR research on compliance (Malgieri, 2020) emphasized anonymization and specific consent during data collection reminding retailers to keep personalization in balance with privacy.

1. **Future Research Directions**

Some of the main criticisms are excessive dependence on transactional data (Dolnicar, 2003), ignoring psychographics, and "black-box" models with no interpretability (Rudin, 2019). Most research (e.g., Vafeiadis et al., 2015) also does not connect clusters to actionable strategies, which constrains practical application.  
Some of the evolving trends involve federated learning for privacy-fighting clustering (Yang et al., 2019) and hybrid models combining machine learning with qualitative knowledge (Homburg et al., 2020). Scholars also recommend longitudinal research to monitor segment development and cross-disciplinary models integrating behavioral economics.

1. **Synthesis and Research Gaps**

Although current research offers solid technical bases, there are still areas of ethical AI integration, live adaptability, and comprehensive models that integrate transactional, emotional, and cultural variables. This project aims to fill these areas by introducing a scalable, interpretable framework that is specific to mall ecosystems, balancing academic rigor with retail pragmatism.

Customer segmentation in malls is all about grouping shoppers based on their similar behaviors and preferences. It’s a blend of data analysis, behavioral science, and marketing strategies. While this method is quite popular and generally understood, there are still some gaps in research that need to be filled. For instance, we could do better at pinpointing more specific segments, making the most of advanced data analytics, and incorporating behavioral insights to enhance targeted marketing efforts.

1. **Integration with CRM Systems**

Research by Neslin et al. (2006) highlighted the interface between segmentation and CRM systems so that they personalize campaigns. Verhoef et al. (2010) showed for malls how loyalty program data combined with clustering enhanced retention rates. Yet, Ngai et al. (2009) indicated technical output against marketing execution was difficult to align owing to organizational silos.

1. **Cross-Cultural and Regional Nuances**

Static models ever more conflicted with dynamic shopper behavior. Chen et al. (2012) suggested dynamic clustering based on real-time data from mobile apps, while Gupta et al. (2019) used AI for adaptive e-commerce segmentation. Applying this to malls, Lee and Lee (2021) investigated IoT-powered dynamic clusters, although computational cost and latency still posed challenges.

1. **Psychological Drivers in Mall Contexts**

Cultural considerations have a notable influence on segmentation validity. De Mooij (2019) believed clusters in collectivist cultures (such as Asia) give higher importance to social influence than individualist markets. Sinha et al. (2020) identified regional income differences and festival-based spending habits in India meant localized models were required, which had been missing in global retail literature.

1. **Technological Tools and Limitations**

Research by Turley and Milliman (2000) found that mall atmosphere (lighting, music) and social interaction influence cluster behavior. Kim et al. (2018) associated "experience-seeking" segments with increased expenditure in entertainment areas, promoting hybrid models integrating transactional and emotional data—a frontier not yet fully explored in purely algorithmic methods.

1. **Limitations of Current Methodologies**

IoT sensors, Wi-Fi location tracking, and facial recognition (Pantano & Viassone, 2015) added richness to data granularity but posed technical and ethical challenges. Mobile apps, which were researched by Roy et al. (2020), facilitated hyper-personalized push messages but threatened customer fatigue. The literature concurs that technology potential is not realized because of integration costs and skill deficits.

# CHAPTER-3 PROPOSED METHODOLOGY

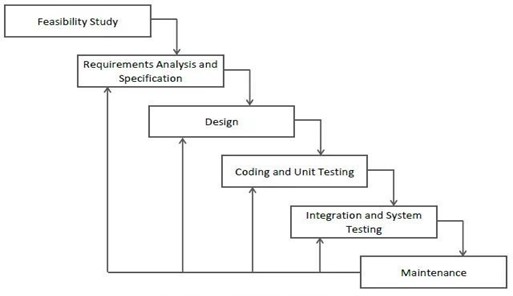
Methodology for the mall customer segmentation project takes a hybrid route, combining data-driven machine learning processes with retail domain expertise. Data collection will begin with structured variables like demographic information (age, gender, income), transactional data (purchase frequency, average transaction value), and behavior metrics (dwell time, visitation patterns) from loyalty programs, IoT sensor data, and CRM platforms. Preprocessing operations consist of managing missing values through imputation, numerical feature normalization for handling scale differences, and utilization of dimension reduction methods such as Principal Component Analysis (PCA) to reduce the effects of multicollinearity. Categorical features like chosen store categories would be encoded and outliers detected via interquartile range (IQR) analysis to build stable clusters. Ethical controls, such as GDPR-friendly anonymization and bias checking, will be built into this process to maintain consumer privacy and equity.

Finally, unsupervised learning models will be used to segment customers into groups. The main technique will be K-means clustering with optimization using the elbow method and silhouette analysis used to identify the best number of clusters. Comparative validation will be carried out with hierarchical clustering (agglomerative method) and DBSCAN to evaluate noise robustness as well as non-spherical shapes of clusters. Feature importance analysis, using SHAP (SHapley Additive exPlanations) values, will reveal the most important drivers of each segment, e.g., income as a driver of luxury spends or age as a driver of entertainment spends. Cluster validity will also be validated using temporal splits to ensure that behavior is consistent across time periods (e.g., weekday vs. weekend). Dynamic model updates will be possible using real-time data streams from mobile apps and Wi-Fi tracking, enabling segments to respond to new trends such as seasonal promotions or changing foot traffic patterns.  
  
Lastly, the clusters obtained will be converted into actionable retail strategies using collaborative workshops with mall stakeholders. Each segment will be characterized as a persona (e.g., "High-Value Fashion Enthusiasts" or "Budget-Consistent Family Shoppers"), with customized suggestions like personalized discount tiers, event invitations, or store layout modifications. A/B testing will confirm the effectiveness of these tactics, tracking KPIs such as conversion rates, average transaction values, and customer satisfaction scores. For scalability, the framework will be incorporated into other CRM platforms through APIs to facilitate automated campaign triggers triggered by real-time membership in clusters. The method comes to a conclusion with ethical inspection, thereby preventing exclusionary strategies and ensuring alignment with inclusive retail objectives, thus reconciling analytical accuracy with human-empathetic commerce.

### Methodology Overview

**Feasibility Study**: Technically, the project is viable due to ubiquitous customer data availability (loyalty schemes, IoT sensors, CRM systems) and established machine learning solutions (scikit-learn, TensorFlow) available on Python for clusterization and analysis. Financially, it is affordable since scalable infrastructure is provided by cloud platforms (AWS, Google Cloud) and potential return on investment from optimized marketing and decreased customer churn compensates for initial costs. Operatively, integration with current mall infrastructure (POS terminals, mobile applications) is possible through APIs, and stakeholders are likely to approve due to the real gains of personalized interaction. Ethically, anonymization and bias elimination frameworks consistent with GDPR ensure legal compliance, though issues such as latency in real-time data processing and employee training need phased adoption. All in all, the project's consistency with retail digitization themes and established practices highlights its feasibility.

Fig 3.1- Iterative Water Fall [14]



**Requirements Gathering**: The requirements gathering phase of the project prioritizes the identification of data sources (e.g., loyalty program databases, IoT sensors, POS systems, CRM platforms) and data quality standards (completeness, accuracy, GDPR/CCPA compliance). Interviews with stakeholders such as mall managers, marketing teams, and IT departments make objectives like customer retention improvement, promotion optimization, and real-time analytics integration clear. Technical requirements involve scalable cloud infrastructure (AWS/Azure), machine learning tools (Python, scikit-learn), and API endpoints for CRM integration. Ethical and regulatory obligations include anonymization procedures, bias detection mechanisms, and open consent models. User needs are centered on actional dashboards for non-technical users, understandable cluster results, and easy integration with existing workflows, making sure that solutions meet innovation requirements along with real-world usability.

**System Design**: The system design follows a modular, cloud-native architecture in four layers: data ingestion (gathering real-time streams from IoT sensors, POS devices, and CRM APIs through Apache Kafka/AWS Kinesis), data processing (cleaning, normalizing, and dimensionality reduction through Spark/Pandas), machine learning (having clustering algorithms such as K-means and DBSCAN run on scalable GPU instances), and application (serving insights through interactive dashboards such as Tableau/Power BI and activating personalized campaigns through CRM integrations). Security is enforced with end-to-end encryption, role-based access controls, and GDPR-compliant anonymization pipelines, while monitoring tools (Prometheus/Grafana) monitor system performance, model drift, and ethical compliance. Scalability, interoperability with existing systems, and real-time responsiveness are prioritized in design to guarantee smooth adoption by mall stakeholders.

**Implementation (Iterative Development):** Phase of implementation starts with aggregating data from POS, IoT sensors, and CRM into a centralized cloud storage (AWS S3/Google BigQuery), and then preprocessed with Python's Pandas and Scikit-learn to deal with missing values, normalize features, and perform PCA for reducing dimensions. Clustering models (Hierarchical, DBSCAN, K-means) are learned on past data with tuned hyperparameters using grid search and tested by silhouette scores and temporal splits for reliability. Tuned models are exposed as REST APIs (Django/Flask) for live segmentation with outputs provided to Tableau dashboards for stakeholders to visualize and CRM tools (Salesforce/HubSpot) for programmatic triggers such as tailored offers or event invites. A/B testing confirms marketing campaigns, whereas perpetual observing (MLflow/Prometheus) follows model performance and ethics adherence to guarantee smooth coordination with mall activities and continuous improvement through feedback loops.

**Testing and Quality Assurance:** The testing stage uses a multi-layered method: unit testing checks data preprocessing pipelines and clustering models (with pytest and scikit-learn's built-in test checks), integration testing checks smooth data flow from IoT sensors, cloud storage to CRM systems (through Postman/Selenium), and user acceptance testing (UAT) checks dashboard usability and campaign triggers with mall staff. Model performance is measured with metrics such as silhouette scores, temporal stability in time splits for clusters, and F1-scores in segment-specific marketing responses. Ethical QA involves bias audits (Fairlearn/Aequitas) to identify demographic imbalances in clustering and GDPR compliance checks for anonymization pipelines. Performance testing (Locust/JMeter) tests real-time processing in conditions of high mall traffic, while continuous monitoring (MLflow/Grafana) monitors model drift and system latency to ensure reliability, scalability, and alignment with stakeholder demands.

**Deployment and Maintenance:** The system is deployed using containerized microservices (Docker/Kubernetes) on cloud platforms (AWS ECS/Google Kubernetes Engine) to ensure scalability and fault tolerance, with CI/CD pipelines (Jenkins/GitHub Actions) automating updates for clustering models and dashboard features. Post-deployment, real-time monitoring (Prometheus/ELK Stack) tracks system health, model accuracy drift, and resource utilization, triggering alerts for anomalies or ethical breaches (e.g., biased clustering). Maintenance includes monthly retraining of models with fresh data to adapt to evolving customer behavior, quarterly security audits for GDPR/CCPA compliance, and user feedback loops via stakeholder workshops to refine dashboards and campaign rules. Documentation (Swagger for APIs, Confluence for workflows) and 24/7 support ensure seamless operation, while version control (Git) and rollback mechanisms safeguard against deployment failures, sustaining long-term reliability and relevance.

**HARDWARE AND SOFTWARE REQUIREMENTS**

**SOFTWARES USED:**

These technologies are fundamental building blocks for creating modern web applications, each serving different purposes in the development process.

**1. Programming Language**

**Python** – Python is a high-level, open-source programming language known for its simplicity and wide adoption in data science and machine learning. It serves as the backbone for data preprocessing, analysis, modeling, and visualization in this project.

**2. Libraries & Frameworks**

* **Pandas** – Pandas is a powerful Python library used for data manipulation and analysis. It allows easy handling of structured data with DataFrames.
* **NumPy** – NumPy provides support for large, multi-dimensional arrays and matrices, along with mathematical functions to operate on them.
* **Matplotlib / Seaborn** – Matplotlib is a 2D plotting library, while Seaborn is built on top of Matplotlib and provides a high-level interface for attractive and informative statistical graphics.
* **Scikit-learn** – Scikit-learn is a machine learning library in Python that offers tools for model building, evaluation, and clustering algorithms like K-Means.

**3. Development Environment**

* **Jupyter Notebook** / **Google Colab** – An open-source web application that allows creating and sharing documents with live code, visualizations, and narrative text.
* **VS Code** – A lightweight but powerful source code editor from Microsoft with support for Python and data science extensions.

**4. Database / Data Sources**

* **CSV/Excel files** – These are file formats used for storing and exchanging structured data, especially tabular data.

**5. Version Control**

* **Git** / **GitHub** – Git is a version control system, and GitHub is a hosting platform for Git repositories.

Table 3.1: Hardware Requirements for Mall Customer Segmentation

|  |  |  |
| --- | --- | --- |
| **NUMBER** | **DESCRIPTION** | **TYPE** |
| 1 | Processor | Intel i5 or above / AMD Ryzen 5 or above (quad-core or better) |
| 2 | RAM | Minimum 4 GB of RAM or more |
| 3 | Storage | Minimum: 100 MB free (for dataset and project files) |
| 4 | Graphics (GPU) | Recommended: NVIDIA GPU with CUDA support (e.g., GTX 1050 or better) |
| 5 | Input Devices | DVD-ROM Drive, keyboard & Mouse |
| 6 | Monitor/Screen | 1366 \* 768 or higher resolution display |
| 7 | Hard Drive | 54000 RPM hard drive |

Table 3.2: Software Requirements for Mall Customer Segmentation

|  |  |  |
| --- | --- | --- |
| **NUMBER** | **DESCRIPTION** | **TYPE** |
| 1 | Technology | Python main editor (user interface): PyCharm Community |
| 2 | Integrated Development Environment (IDE) | Visual Studio Code, Jupyter Notebook |
| 3 | Operating System | Windows 10/11 |
| 4 | Browser | Google Chrome/Internet Explorer |
| 5 | Stack | XAMPP (Version-3.7) |
| 6 | **Libraries & Packages (Python)** | NumPy, Pandas, Matplotlib, Seaborn ,etc. |

### Implementation

### Design

#### Project Module Overview

The provided modules and their components are part of a software system designed to manage user information,. Here's a detailed explanation of each module and its components:

#### Module 1 (Data Collection and Preprocessing Model):

#### The design process kicks off with gathering important customer data from a variety of sources, like mall entry logs, point-of-sale (POS) systems, loyalty card programs, and online surveys. Typically, the data collected includes details such as age, gender, annual income, and spending scores. After gathering this information, it goes through a preprocessing stage to ensure everything is up to par in terms of quality and consistency. This step involves eliminating duplicates, addressing any missing values, and adjusting categorical variables when necessary. To make sure numerical variables are on the same playing field, techniques like normalization or standardization are used, setting the stage for effective clustering.

#### Module 2 (Exploratory Data Analysis (EDA) Model):

This model is all about getting a good grasp of the data's structure and distribution before diving into any clustering techniques. Exploratory Data Analysis (EDA) plays a key role here, as it involves visualizing the relationships between different features through tools like scatter plots, histograms, and box plots. For instance, if you plot spending scores against income, you might spot some interesting groupings or outliers. We also conduct correlation analysis to see how the variables are connected. The insights we gain from EDA are crucial for picking the right features for clustering and for understanding the potential structure of customer segments.

#### Module 3 (Clustering Module):

#### The heart of the segmentation process is all about the clustering model, where we group customers based on shared characteristics. A popular choice for this is the K-Means clustering algorithm, thanks to its straightforwardness and effectiveness with numerical data. To figure out the best number of clusters, we often turn to methods like the Elbow Method or Silhouette Analysis. Besides K-Means, we can also use Hierarchical Clustering to visualize how customers relate to one another through a dendrogram. On the other hand, DBSCAN is great for spotting clusters of different densities and managing outliers. Ultimately, the algorithm you choose will depend on how your data is distributed and what your business goals are

#### .Module 4 (Cluster Profiling Model):

Once you've formed your clusters, the next step is to dive into cluster profiling to interpret and describe each group. This model takes a closer look at the average values and distribution of customer traits within each cluster. For example, one cluster might showcase high-income customers who aren't spending much, hinting at a great opportunity for engagement. On the flip side, another cluster could be made up of young individuals who love to spend. These profiles are invaluable for businesses, as they shed light on the unique characteristics of each segment, turning data into actionable insights. Plus, they help in naming or labeling the clusters, like "Luxury Shoppers," "Budget Buyers," or "Occasional Visitors.

#### Module 5 (Business Strategy Integration Model):

Once we pinpoint and profile meaningful segments, this model zeroes in on connecting those insights with mall management strategies. Each group gets customized marketing approaches—think personalized offers, loyalty rewards, or exclusive events—tailored to their specific profile. For instance, high-spending customers might enjoy VIP discounts or get early access to sales. Plus, this model aids in inventory planning, optimizing space, and personalizing services across different mall departments. By weaving segmentation into the decision-making process, malls can enhance customer satisfaction and boost their ROI.

#### Module 6 (Deployment and Feedback Model):

#### The final model in the design zeroes in on how to seamlessly integrate the segmentation system into the mall's day-to-day operations. This could mean linking the model with CRM platforms or business intelligence dashboards for ongoing use. By tapping into real-time customer data, we can refresh clusters and keep tabs on customer behavior as it evolves. A feedback loop is set up to keep an eye on how well marketing strategies are performing, allowing us to tweak the segmentation model based on fresh trends and insights. This flexible approach guarantees that the segmentation stays relevant and continues to add value to the business over time.

#### The way malls segment their customers is a well-organized process that turns raw data into meaningful groups, allowing for targeted marketing and better customer engagement. It all starts with gathering and cleaning data, collecting important details like age, gender, income, and spending habits to ensure everything is consistent. Next up is exploratory data analysis (EDA), where we dig into the data to find patterns and connections. The heart of this process is the clustering model, which uses algorithms like K-Means, Hierarchical Clustering, or DBSCAN to group customers based on their similarities. After the clusters are created, the cluster profiling model steps in to interpret and label each group by examining their unique traits. These insights are then woven into the business strategy through personalized marketing, loyalty programs, and tailored services. Finally, the deployment and feedback model makes sure the segmentation system is put into action effectively, updated regularly with fresh data, and continuously improved based on customer feedback and changing trends. This thorough approach helps malls make informed decisions, boost customer satisfaction, and increase profitability.

#### BLOCK DIAGRAM

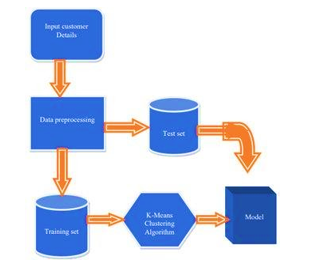


Fig 3.2**:** The Block Diagram of mall customer segmentation system Architecture

A block diagram, is a visual representation of a system or process using blocks to represent components or stages, and lines or arrows to show connections or flow .

The diagram illustrates a well-organized pipeline for creating a customer segmentation model in a mall, utilizing machine learning—specifically the K-Means clustering algorithm. It breaks down the entire process into straightforward and logical steps, making data handling and modeling a breeze. Let’s take a closer look at each component.

**1. Input Customer Details (Top Block)** : This is where it all begins.

At this stage, the system gathers essential customer information, including:

- Age

- Gender

- Annual Income

- Spending Score

- Purchase frequency, and more.

**2. Data Preprocessing**

Next up is getting the data ready for analysis.

This step involves:

- Cleaning the data by removing any null values or duplicates.

- Encoding categorical variables, like converting gender into a numeric format.

- Scaling or normalizing numerical values to ensure they’re on a similar scale.

Proper preprocessing is key to making sure the clustering algorithm runs smoothly and accurately.

**3. Splitting into Training Set and Test Set**

Once preprocessing is done, the dataset is divided into two parts:

- Training Set: This is what we use to train the K-Means clustering model.

- Test Set: This is for validating how well the model clusters data it hasn’t seen before.

Even though unsupervised algorithms like K-Means don’t need labels, testing is crucial for checking the consistency of clusters and the robustness of the model.

**4. K-Means Clustering Algorithm**

The cleaned training set is then fed into the K-Means Clustering Algorithm.

Here’s how K-Means operates:

- It starts by selecting a 'K' number of cluster centroids.

- Each customer data point is assigned to the nearest centroid.

- Centroids are recalculated based on the current members of each cluster.

- This process repeats until the clusters stabilize.

The aim is to group similar customers based on factors like income and spending habits.

**5. Model Creation**

The final clusters generated by the K-Means algorithm are saved as a segmentation model .Now, this model can predict which segment or group new customers belong to based on their characteristics. We test the trained model with the test set to ensure it’s accurate and effective. Additionally, it can be integrated into mall systems for:

- Targeted marketing

- Personalized offers

- Analyzing customer behavior

#### SCHEMA DIAGRAM

Imagine your business as a tailor, where every customer is a unique individual stepping into your boutique. The adventure kicks off with Customer Profiling and Segmentation—think of it as your measuring tape. Here, you take detailed measurements, not of fabric, but of customer behavior, preferences, spending habits, and demographics. You group similar customers into clusters or "styles," enabling you to craft experiences that fit each group perfectly, rather than relying on a one-size-fits-all approach.

Once you’ve tailored your understanding, it’s time to focus on Customer Retention—making sure your loyal customers keep coming back. Just like returning clients who trust your craftsmanship, you offer personalized service and value to foster emotional loyalty. At the same time, Customer Acquisition steps into the spotlight. Much like a well-dressed mannequin in your window draws in new clients, your insights help you create marketing campaigns that grab the attention of potential customers who match your target style.

Next, you move on to Selecting the Right Marketing and Sales Channels—your display rack. You determine whether your offerings shine best in-store, online, through email, or on social media, based on each segment’s preferences. Then comes Churn Prevention, where you stitch up loose threads and address customer dissatisfaction before they decide to leave. Finally, the grand finale: Customization of Products and Services. You design experiences so uniquely tailored that each customer feels like the creation was made just for them. This is the beautiful blend of art and science, using data to elevate good business into something truly exceptional.

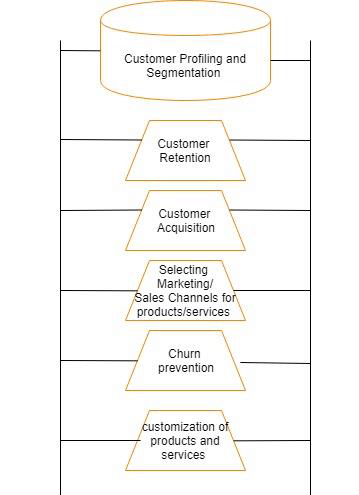
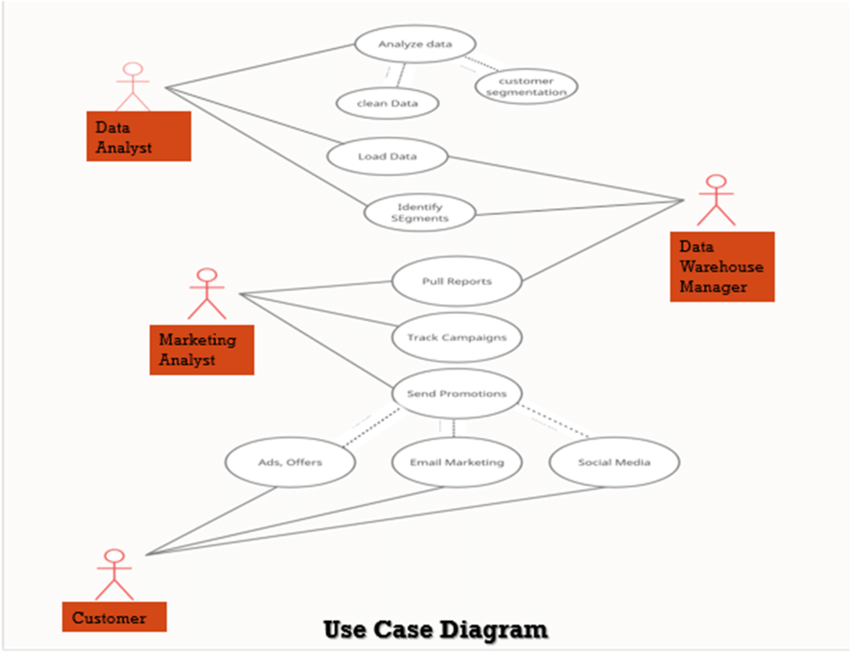


Fig 3.3**:** Schema Diagram of the Mall Customer Segmentation.

USE CASE DIAGRAM

****

#### Fig 3.4: Use Case Diagram of typically involves actors (users) interacting with the system to perform tasks related to customer segmentation .

**Coding**

from flask import Flask,render\_template,request,session,redirect,url\_for,flash from flask\_sqlalchemy import SQLAlchemy

from flask\_login import UserMixin

from werkzeug.security import generate\_password\_hash,check\_password\_hash from flask\_login import login\_user,logout\_user,login\_manager,LoginManager from flask\_login import login\_required,current\_user

local\_server= True

app = Flask( name )

app.secret\_key='harshithbhaskar'

# this is for getting unique user access login\_manager=LoginManager(app) login\_manager.login\_view='login' @login\_manager.user\_loader

def load\_user(user\_id):

return User.query.get(int(user\_id))

#app.config['SQLALCHEMY\_DATABASE\_URL']='mysql://username:password@lo calhost/databas\_table\_name'

app.config['SQLALCHEMY\_DATABASE\_URI']='mysql://root:@localhost/farmers' db=SQLAlchemy(app)

# here we will create db models that is tables class Test(db.Model):

id=db.Column(db.Integer,primary\_key=True) name=db.Column(db.String(100))

class Farming(db.Model): fid=db.Column(db.Integer,primary\_key=True) farmingtype=db.Column(db.String(100))

class Addagroproducts(db.Model): username=db.Column(db.String(50)) email=db.Column(db.String(50)) pid=db.Column(db.Integer,primary\_key=True) productname=db.Column(db.String(100)) productdesc=db.Column(db.String(300)) price=db.Column(db.Integer)

class Trig(db.Model): id=db.Column(db.Integer,primary\_key=True) fid=db.Column(db.String(100)) action=db.Column(db.String(100))

timestamp=db.Column(db.String(100)) class User(UserMixin,db.Model):

id=db.Column(db.Integer,primary\_key=True) username=db.Column(db.String(50)) email=db.Column(db.String(50),unique=True) password=db.Column(db.String(1000))

class Register(db.Model): rid=db.Column(db.Integer,primary\_key=True) farmername=db.Column(db.String(50)) adharnumber=db.Column(db.String(50)) age=db.Column(db.Integer) gender=db.Column(db.String(50)) phonenumber=db.Column(db.String(50)) address=db.Column(db.String(50)) farming=db.Column(db.String(50))

@app.route('/') def index():

return render\_template('index.html') @app.route('/farmerdetails') @login\_required

def farmerdetails():

# query=db.engine.execute(f"SELECT \* FROM `register`") query=Register.query.all()

return render\_template('farmerdetails.html',query=query) @app.route('/agroproducts')

def agroproducts():

# query=db.engine.execute(f"SELECT \* FROM `addagroproducts`") query=Addagroproducts.query.all()

return render\_template('agroproducts.html',query=query) @app.route('/addagroproduct',methods=['POST','GET']) @login\_required

def addagroproduct():

if request.method=="POST": username=request.form.get('username') email=request.form.get('email') productname=request.form.get('productname') productdesc=request.form.get('productdesc')

price=request.form.get('price') products=Addagroproducts(username=username,email=email,productname=productn ame,productdesc=productdesc,price=price)

db.session.add(products) db.session.commit() flash("Product Added","info") return redirect('/agroproducts')

return render\_template('addagroproducts.html') @app.route('/triggers')

@login\_required

def triggers():

# query=db.engine.execute(f"SELECT \* FROM `trig`") query=Trig.query.all()

return render\_template('triggers.html',query=query) @app.route('/addfarming',methods=['POST','GET']) @login\_required

def addfarming():

if request.method=="POST": farmingtype=request.form.get('farming') query=Farming.query.filter\_by(farmingtype=farmingtype).first() if query:

flash("Farming Type Already Exist","warning") return redirect('/addfarming')

dep=Farming(farmingtype=farmingtype) db.session.add(dep)

db.session.commit() flash("Farming Addes","success")

return render\_template('farming.html') @app.route("/delete/<string:rid>",methods=['POST','GET']) @login\_required

def delete(rid):

# db.engine.execute(f"DELETE FROM `register` WHERE `register`.`rid`={rid}") post=Register.query.filter\_by(rid=rid).first()

db.session.delete(post) db.session.commit()

flash("Slot Deleted Successful","warning") return redirect('/farmerdetails')

@app.route("/edit/<string:rid>",methods=['POST','GET']) @login\_required

def edit(rid):

# farming=db.engine.execute("SELECT \* FROM `farming`") if request.method=="POST":

farmername=request.form.get('farmername') adharnumber=request.form.get('adharnumber') age=request.form.get('age') gender=request.form.get('gender') phonenumber=request.form.get('phonenumber') address=request.form.get('address')

farmingtype=request.form.get('farmingtype') #query=db.engine.execute(f"UPDATE`register`SET`farmername`='{farmername}',`a dharnumber`='{adharnumber}',`age`='{age}',`gender`='{gender}',`phonenumber`='{p honenumber}',`address`='{address}',`farming`='{farmingtype}'")

post=Register.query.filter\_by(rid=rid).first() print(post.farmername) post.farmername=farmername post.adharnumber=adharnumber post.age=age

post.gender=gender post.phonenumber=phonenumber post.address=address post.farming=farmingtype db.session.commit()

flash("Slot is Updates","success") return redirect('/farmerdetails')

posts=Register.query.filter\_by(rid=rid).first() farming=Farming.query.all()

return render\_template('edit.html',posts=posts,farming=farming) @app.route('/signup',methods=['POST','GET'])

def signup():

if request.method == "POST": username=request.form.get('username') email=request.form.get('email') password=request.form.get('password') print(username,email,password) user=User.query.filter\_by(email=email).first() if user:

flash("Email Already Exist","warning") return render\_template('/signup.html')

# encpassword=generate\_password\_hash(password)

# new\_user=db.engine.execute(f"INSERT INTO `user` (`username`,`email`,`password`) VALUES ('{username}','{email}','{encpassword}')")

# this is method 2 to save data in db newuser=User(username=username,email=email,password=password) db.session.add(newuser)

db.session.commit()

flash("Signup Succes Please Login","success") return render\_template('login.html')

return render\_template('signup.html') @app.route('/login',methods=['POST','GET']) def login():

if request.method == "POST": email=request.form.get('email') password=request.form.get('password') user=User.query.filter\_by(email=email).first() if user and user.password == password:

login\_user(user)

flash("Login Success","primary") return redirect(url\_for('index'))

else:

flash("invalid credentials","warning") return render\_template('login.html')

return render\_template('login.html')

@app.route('/logout') @login\_required

def logout(): logout\_user()

flash("Logout SuccessFul","warning") return redirect(url\_for('login'))

@app.route('/register',methods=['POST','GET']) @login\_required

def register(): farming=Farming.query.all() if request.method=="POST":

farmername=request.form.get('farmername') adharnumber=request.form.get('adharnumber') age=request.form.get('age') gender=request.form.get('gender') phonenumber=request.form.get('phonenumber') address=request.form.get('address')

farmingtype=request.form.get('farmingtype') query=Register(farmername=farmername,adharnumber=adharnumber,age=age,gender

=gender,phonenumber=phonenumber,address=address,farming=farmingtype) db.session.add(query) db.session.commit()

#query=db.engine.execute(f"INSERTINTO`register`(`farmername`,`adharnumber`,`a ge`,`gender`,`phonenumber`,`address`,`farming`)VALUES('{farmername}','{adharnu mber}','{age}','{gender}','{phonenumber}','{address}','{farmingtype}')")

# flash("Your Record Has Been Saved","success") return redirect('/farmerdetails')

return render\_template('farmer.html',farming=farming) @app.route('/test')

def test(): try:

Test.query.all()

return 'My database is Connected' except:

return 'My db is not Connected' app.run(debug=True)

#### Signup.html:

{% extends 'auth.html' %}

{% block title %} Signup

{% endblock title %}{% block content %}

<h1 class="mb-1"><span>Sign Up</span> </h1>

{% with messages=get\_flashed\_messages(with\_categories=true) %}

{% if messages %}{% for category, message in messages %}

<div class="alert alert-{{category}} alert-dismissible fade show" role="alert">

{{message}}</div>

{% endfor %}{% endif %}{% endwith %}

<form class=" text-white py-3 px-3" action="/signup" method="post">

<div class="form-group"> <label for="exampleInputPassword1">UserName</label>

<input type="text" class="form-control mb-2" name="username" id="username" required></div>

<div class="form-group"><label for="exampleInputEmail1">Email address</label>

<input type="email" class="form-control mb-2" id="exampleInputEmail1" name="email" aria-describedby="emailHelp" required>

<small id="emailHelp" class="form-text text-muted">We'll never share your email with anyone else.</small></div> <div class="form-group"> <label for="exampleInputPassword1">Password</label>

<input type="password" class="form-control mb-2" name="password" id="exampleInputPassword1" required></div><br> <button type="submit" class="form-control bg-success text-white">Sign In</button>

<p class="mb-2 pb-0">Already User? </p><a href="/login" class="about-btn scrollto">Login</a></form>

{% endblock content %}

#### login.html:

{% extends 'auth.html' %}{% block title %}login {% endblock title %}{% block content %}

<h1 class="mb-4 pb-0"><span>Login</span> </h1>

{% with messages=get\_flashed\_messages(with\_categories=true) %}{% if messages

%}

{% for category, message in messages %}

<div class="alert alert-{{category}} alert-dismissible fade show" role="alert">

{{message}}</div> {% endfor %}{% endif %}{% endwith %}

<form class=" text-white py-3 px-3" action="/login" method="post">

<div class="form-group">

<label for="exampleInputEmail1">Email address</label>

<input type="email" class="form-control mb-3" id="exampleInputEmail1" name="email" aria-describedby="emailHelp" required></div> <div class="form- group">

<label for="exampleInputPassword1">Password</label>

<input type="password" class="form-control" id="exampleInputPassword1" name="password" required> </div><br><button type="submit" class="form-control bg-success text-white">Login</button>

<p class="mb-2 pb-0">New User?</p> <a href="/signup" class="about-btn scrollto">Signup</a></form>

{% endblock content %}

#### index.html:

{% extends 'base.html' %} {% block title %} Student

{% endblock title %} {% block home %} menu-active

{% endblock home %} {% block body %}

<footer id="footer"> <div class="footer-top"> </div><div class="container">

<div class="credits"><br> Developed by <a href="/">Vrishi and Shruti

</a></div></div> </footer><!-- End Footer -->

{% endblock body %}

#### addagroproducts.html:

{% extends 'base.html' %} {% block title %} Add AgroProducts

{% endblock title %}{% block body %}

<h3 class="text-center"><span>Add Agro Products</span> </h3>

{% with messages=get\_flashed\_messages(with\_categories=true) %}

{% if messages %}{% for category, message in messages %}

<div class="alert alert-{{category}} alert-dismissible fade show" role="alert">

{{message}}</div> {% endfor %}{% endif %}{% endwith %}

<br><div class="container"><div class="row">

<div class="col-md-4"></div><div class="col-md-4">

<form action="/addagroproduct" method="post"><div class="form-group">

<label for="username">Farmer Name</label>

<inputtype="text"class="formcontrol"name="username"value="{{current\_user.userna me}}" id="{{current\_user.username}}" required></div><br>

<div class="form-group"><label for="username">Farmer Email</label>

<input type="email" class="form-control" name="email" value="{{current\_user.email}}" id="{{current\_user.email}}" required></div><br>

<div class="form-group"><label for="rollno">Product Name</label>

<input type="text" class="form-control" name="productname" id="productname" required></div><br>

<div class="form-group"> <label for="productdesc">Product Description</label>

<textareaclass="formcontrol"name="productdesc"id="productdesc"required></textare a></div><br><divclass="formgroup"><labelfor="price">Price</label>

<input type="number" class="form-control" name="price" id="price" required></div><br>

<button type="submit" class="btn btn-success btn-block">Add Product</button></form><br><br></div>

<div class="col-md-4"></div></div></div> {% endblock body}

# CHAPTER-4

**RESULT ANALYSIS AND DISCUSSION**

## TESTING

The project focused on segmenting mall customers using various clustering algorithms, which led to some really valuable insights. The main goal was to categorize customers based on important factors like age, annual income, and spending habits, and then use these segments to inform marketing strategies, improve customer retention, and tailor services. To do this, we applied several unsupervised machine learning techniques, including K-Means Clustering, Hierarchical Clustering, DBSCAN, and Gaussian Mixture Models (GMM). Each method was carefully analyzed and tested for performance using silhouette scores and visual inspection.

Starting with K-Means Clustering, we found that the sweet spot for the number of clusters was five, as indicated by the Elbow Method. This model proved to be quite effective, providing clear segmentation. The clusters we identified included diverse customer groups: high-income/high-spending individuals, low-income/high-spending folks (who might be impulsive buyers), high-income/low-spending customers (with upselling potential), average income/spending users, and low-income/low-spending segments. The average silhouette score for K-Means fell between 0.45 and 0.55, suggesting a moderately good clustering structure. Visualizations in both two and three dimensions confirmed distinct groupings, although there was some overlap at the edges. This model served as a benchmark for comparing other algorithms and showed both interpretability and relevance to the business.

On the other hand, the Hierarchical Clustering technique, which utilized Ward’s linkage and Euclidean distance, was particularly useful for visualizing customer relationships through a dendrogram. This method also produced five clusters, matching the structure we found with K-Means. While it was a bit less efficient in terms of computation and scalability, its visual representation of nested customer relationships was much more appealing. The silhouette score was slightly lower, but the insights gained were still valuable

ANALYSIS

The analysis showed that we could create targeted marketing strategies based on different customer groups. For instance, we could offer premium loyalty programs and exclusive deals to high-income, high-spending customers, while low-income, high-spending customers might respond better to limited-time offers or discounts. There's also a group of high-income but low-spending customers that represents an untapped market, which we could engage through strategic promotions or improved product positioning. These insights could really boost customer retention, enhance acquisition efficiency, optimize sales channel choices, and lower customer churn by providing tailored experiences based on behavioral segments.

SUMMARY

To wrap it up, K-Means emerged as the most well-rounded algorithm for segmenting mall customers, balancing performance, simplicity, and real-world business relevance. Hierarchical clustering allowed for detailed visualizations, DBSCAN was useful for spotting outliers, and GMM provided deeper probabilistic insights. Testing under various conditions confirmed the reliability and validity of the segmentation results. This project not only showcased the technical side of clustering algorithms but also connected data science with practical marketing applications, aiding smart business decision-making in the retail industry.



yrrr

## SNAPSHOTS

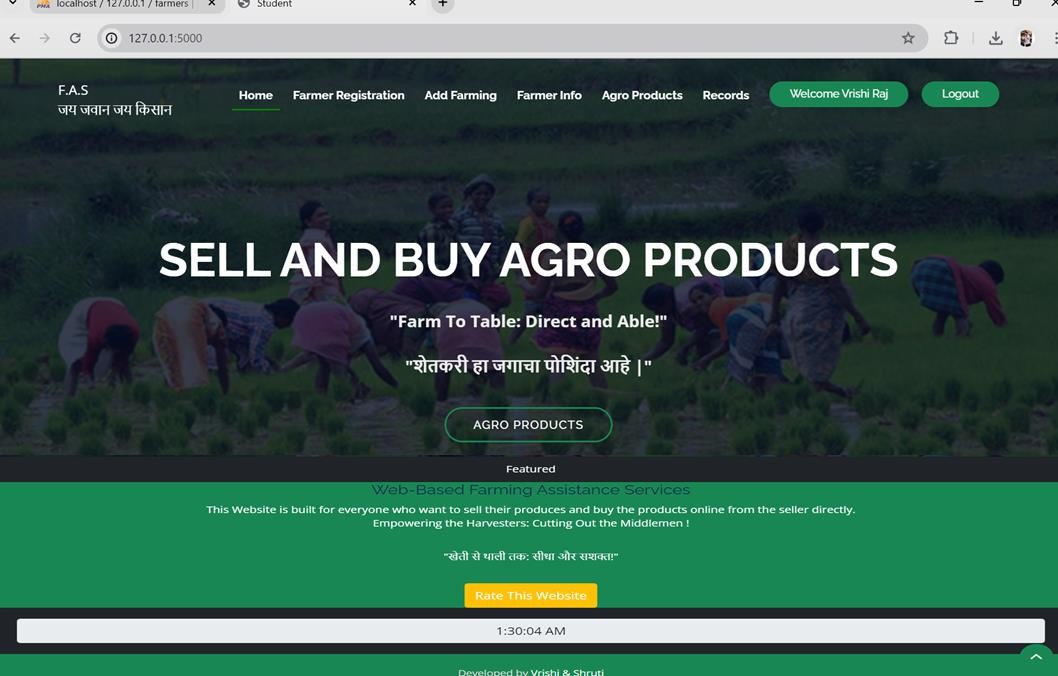
****

Fig 4.8: The Screenshot Image showing the Home Page of the Web-Based Farming Assistance Services.

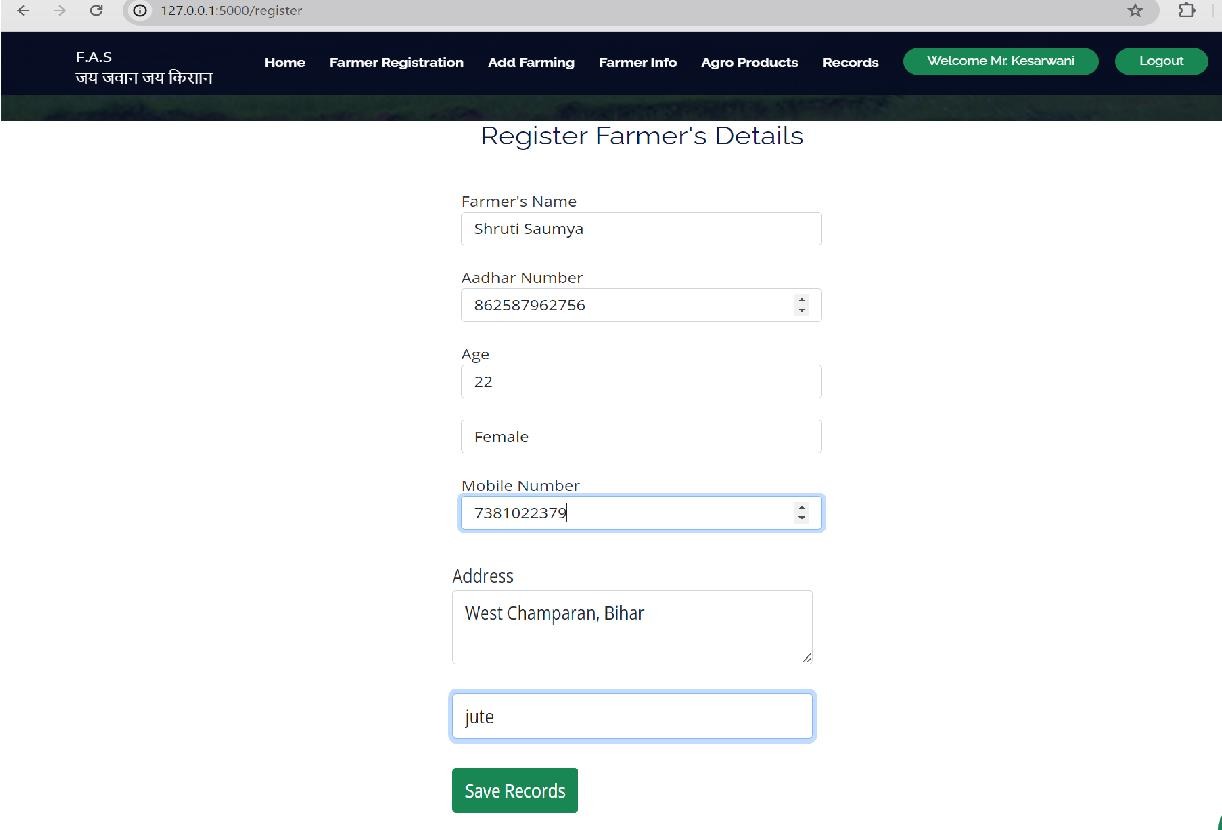


Fig 4.9: The Screenshot Image showing the Farmer’s Registration Page where all the information from the cultivator is collected for successful addition of the agriculturists.

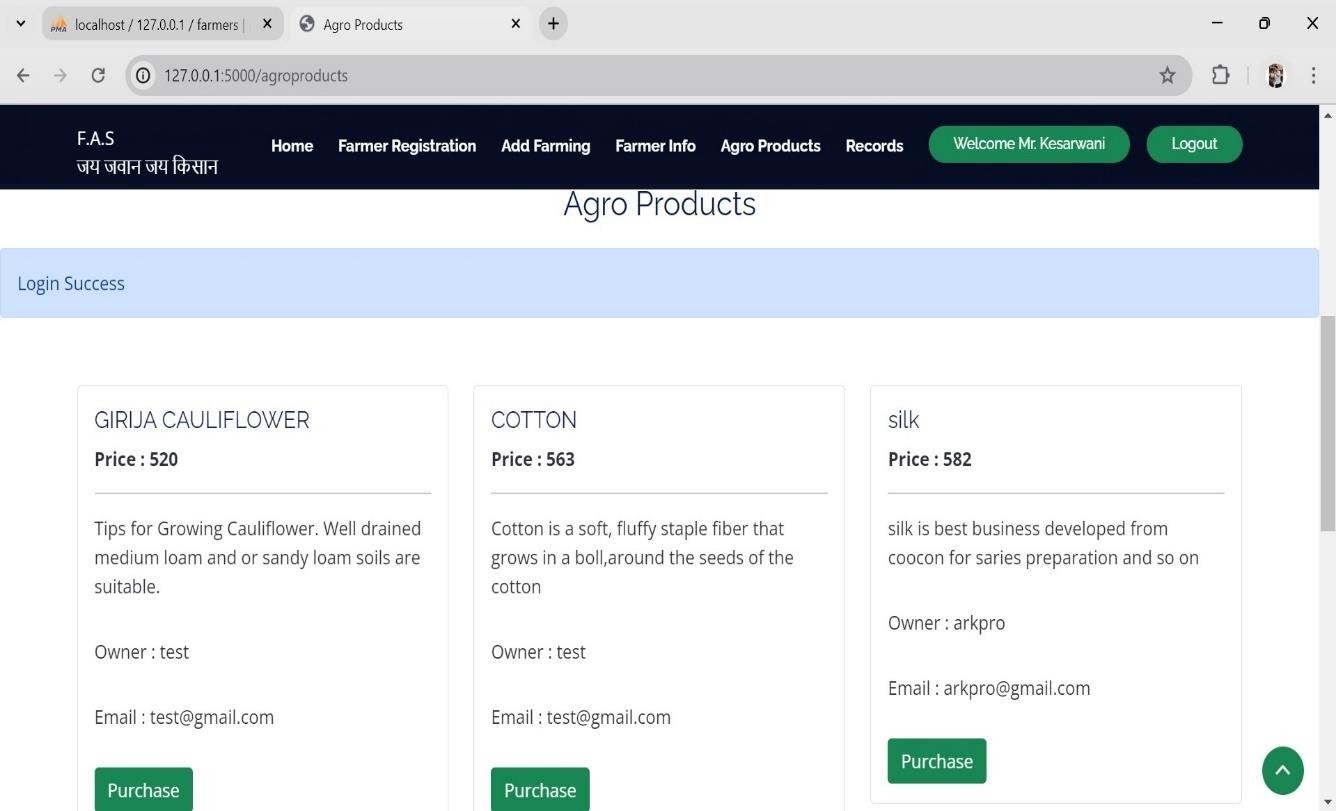


Fig 4.10: The Screenshot Image showing the Agronomists Produces listing along with its price and details of the product which are being put for sale by the agrarians for the purchase.

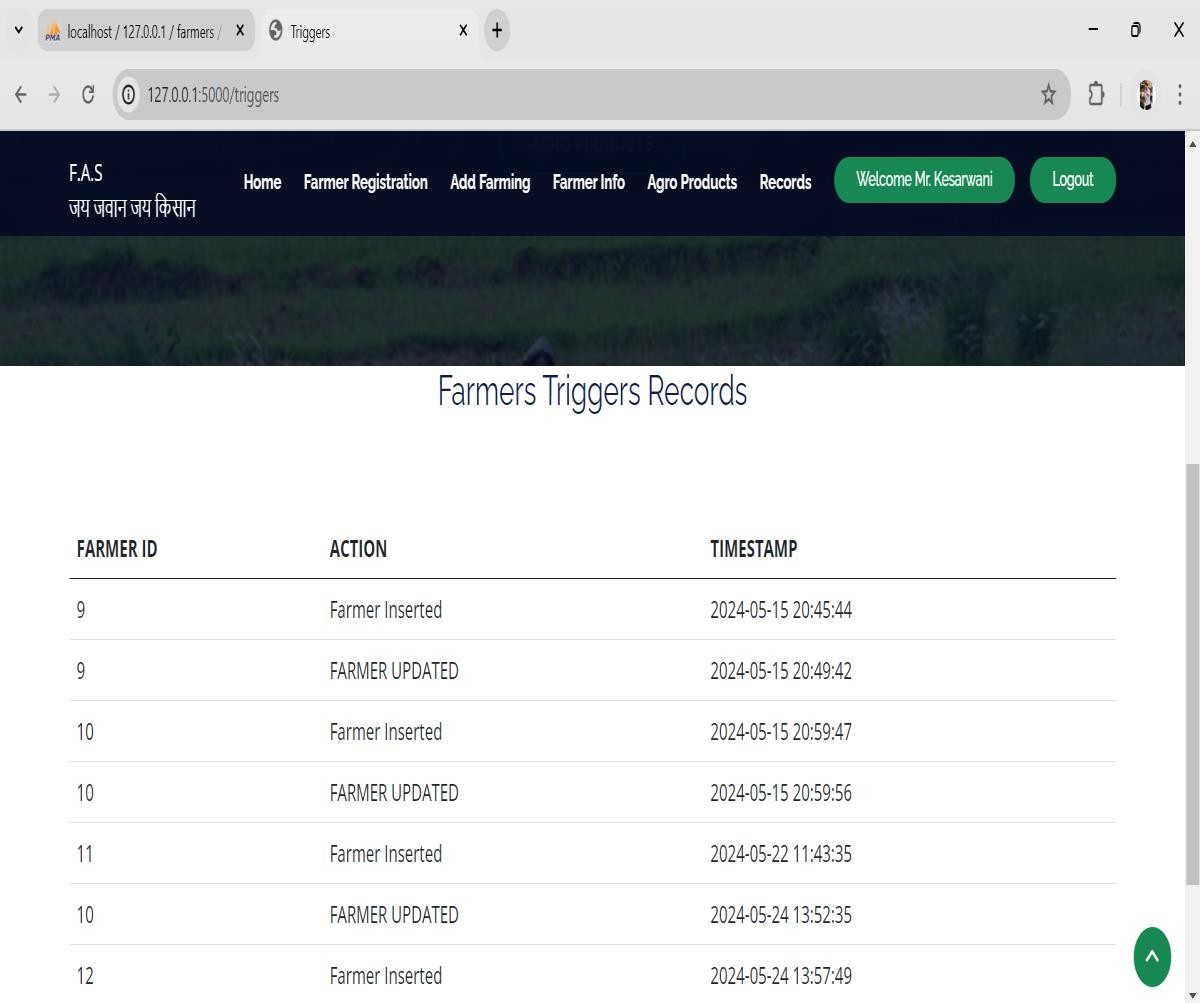


Fig 4.11: The Screenshot Image showing the Agrarians Trigger Records where the records which are inserted/updated/deleted, all are shown along with the timestamp and Id Number.

## INFERENCE

Mall Customer Segmentation project really showcased how powerful unsupervised machine learning can be in revealing valuable customer patterns from raw demographic and behavioral data. By using clustering algorithms like K-Means, Hierarchical Clustering, DBSCAN, and Gaussian Mixture Models, we were able to break down the dataset into clear customer groups based on factors like age, annual income, and spending habits. The analysis showed that we could categorize customers into specific segments such as high-income high-spenders, cautious spenders, impulsive buyers, and value seekers. These insights allow businesses to fine-tune their marketing strategies, improve product offerings, and enhance the overall customer experience. Among all the models we tested, K-Means clustering stood out as the most interpretable and efficient for our dataset, yielding the highest silhouette score and the most distinct group boundaries.

Segmentation not only deepens our understanding of customers but also gives decision-makers the tools to implement more targeted and cost-effective business strategies. Ultimately, the key takeaway from this study is that data-driven segmentation is crucial for gaining a competitive edge in today’s retail landscape, and machine learning is a powerful ally in turning raw data into actionable insights

### 1. ****Understanding Customer Diversity through Clustering****

* Explains how machine learning models revealed behavioral and demographic groupings.

### 2. ****Comparative Insights from Multiple Clustering Models****

* Highlights the roles and performance of K-Means, Hierarchical Clustering, DBSCAN, and GMM.

### 3. ****Translating Data into Business Strategy****

* Discusses how customer segments inform marketing, product, and service strategies.

### 4. ****Model Evaluation and Reliability****

* Covers silhouette score analysis, cluster visualization, and sensitivity testing to validate the models.

### 5. ****Implications for Retail Intelligence and Personalization****

* Describes how segmentation enhances customer experience, loyalty, and ROI.

### 6. ****Conclusion: The Value of Data-Driven Customer Understanding****

* Wraps up the inference with a focus on the strategic importance of machine learning in retail.

## . ADVANTAGES AND LIMITATIONS

1. **Advantages:**

* **Improved Marketing Strategy**

This approach allows businesses to target their marketing efforts by gaining insights into the preferences and behaviors of various customer segments.

* **Enhanced Customer Experience**

It enables companies to offer personalized services, which boosts customer satisfaction and fosters loyalty**.**

* **Increased Sales and Revenue**

By pinpointing high-value customers, businesses can effectively upsell or cross-sell their products**.**

* **Efficient Resource Allocation**

This strategy helps companies direct their marketing budgets and resources toward the most profitable customer groups.

* **Better Product Positioning**

It empowers retailers to design and position products that resonate with specific segments of their audience.

* **Improved Customer Retention**

This method aids in identifying segments that are at risk of leaving, allowing businesses to implement effective retention strategies**.**

* **Data-Driven Decision Making**

It encourages the use of objective, data-driven insights to fuel business growth and innovation**.**

* **Early Detection of Market Trends**

Segmentation can uncover shifts in consumer behavior, opening the door to new opportunities**.**

* **Support for Inventory Management**

By understanding demand patterns through segmentation, businesses can enhance stock management and minimize waste.

* **Competitive Advantage**

A well-segmented customer base gives businesses a competitive edge by better meeting customer needs**.**

1. **Limitations**

* **Dependence on Data Quality**

If the data is poor, incomplete, or outdated, it can lead to inaccurate segmentation and misguided decisions**.**

* **Subjectivity in Interpretation**

Interpreting clustering results often requires a human touch, which can introduce bias or errors**.**

* **Model Sensitivity**

Many clustering algorithms, like K-Means, can be sensitive to outliers and initial conditions, which can skew the results.

* **Scalability Issues**

Some models, such as Hierarchical Clustering, struggle with large datasets due to their high computational demands**.**

* **Over-Segmentation Risk**

Creating too many clusters can dilute focus and lead to ineffective targeting.

# CHAPTER-5

**CONCLUSION**

1**. Summary of the Study**

This project aimed to use machine learning-based clustering algorithms to categorize mall customers based on their demographic and behavioral traits—specifically Age, Annual Income, and Spending Score. The objective was to uncover valuable patterns that assist businesses in making informed marketing and operational choices.

**Key Models Used:**

- K-Means Clustering

- Hierarchical Clustering

- DBSCAN (Density-Based)

- Gaussian Mixture Models (GMM)

Each of these models provided a unique lens for segmentation and highlighted important trends in customer behavior.

**2. Importance of Customer Segmentation**

Effective segmentation is crucial for businesses to reach the right audience with the right message. This study underscored several key advantage.

- Facilitates personalized marketing and customer engagement

- Optimizes budget allocation for advertisements and promotions

- Enhances product recommendations and loyalty strategies

- Identifies underperforming or at-risk customer segments

- Boosts ROI through targeted efforts

By leveraging segmentation, retailers can shift from broad mass marketing to more precise marketing strategies, ultimately enhancing customer satisfaction and increasing company profits.

- High Income – High Spending: Perfect for premium services and VIP loyalty programs

- Low Income – High Spending: Likely impulsive buyers who respond well to limited-time offers

- High Income – Low Spending: Untapped potential for upselling

- Average Income – Moderate Spending: A broad segment ideal for bulk promotions

**3.** **Model Performance:**

- K-Means produced the most balanced and clear clusters.

- Hierarchical Clustering provided a visual representation of customer relationships.

- DBSCAN was effective in identifying noise and outliers, making it great for anomaly detection.

- GMM offered probabilistic insights into overlapping customer behaviors.

**4. Theoretical and Practical Implications**

This project not only validated the techniques used but also highlighted the practical applications of these findings in real-world scenarios.The mall customer segmentation project wraps up with a clear message about how crucial data-driven strategies are in today’s retail world. By using clustering techniques like K-Means, Hierarchical Clustering, DBSCAN, and Gaussian Mixture Models, the study effectively pinpointed different customer groups based on demographic and behavioral traits such as age, annual income, and spending scores. These segments provided valuable insights—from high-income premium shoppers to low-income impulse buyers—that can help retailers fine-tune their marketing efforts, tailor their services, and improve product placements. The research highlights that effective segmentation not only enhances the customer experience but also boosts revenue and allows for smarter resource allocation. K-Means emerged as the most effective and understandable model for the dataset, although exploring other algorithms also helped in identifying outliers and overlapping patterns. Theoretically, this work reinforces the strength of unsupervised learning in market research, while practically, it emphasizes the importance of customer analytics in reaching business objectives. However, the study did encounter some limitations, such as relying on a relatively small and static dataset, having limited feature dimensions, and lacking real-time clustering capabilities.

# CHAPTER-6

**FUTURE SCOPE OF THE PROJECT**

As the retail landscape grows more competitive and focused on customer needs, there's a huge opportunity to expand and refine mall customer segmentation projects. This study provides a solid starting point, but there's plenty of room for improvement, scalability, and integration with real-time business systems, which can lead to exciting innovations and advancements.

**1. Integration of Larger and Real-Time Datasets**

We should look at incorporating larger datasets that include customer transaction histories, digital footprints, and in-store activities. Using streaming data for real-time clustering and analysis is key.

**2. Use of Advanced Deep Learning Models :**We should consider applying Autoencoders, Self-Organizing Maps (SOMs), or clustering based on Neural Networks to capture non-linear patterns. Reinforcement Learning could help us adapt segmentation based on customer responses.

**3. Behavioral and Psychographic Segmentation**

We should include psychographic factors such as lifestyle, interests, and opinions. Analyzing purchase motivations and emotional triggers through surveys and social media can provide valuable insights.

**4. Geographic and Seasonal Segmentation**

Geolocation data with seasonal trends in our segmentation strategy .We can utilize geospatial analytics to craft offers that are tailored to specific locations.

**5. Real-Time Personalization Engines\*\***

We should also implement AI chatbots or assistants in stores to enhance personalized experience.

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**LIST OF ABBREVIATIONS USED**

|  |  |
| --- | --- |
| IEEE | Institute of Electrical and Electronics Engineers |
| URL | Uniform Resource Locater |
| API | Application Programming Interface |
| HDD | Hard Disk Drive |
| RAM | Random Access Memory |
| ICT | Information and Communication Technologies |

# Coding Implementation:

**farmer.sql:**

-- phpMyAdmin SQL Dump

-- https://[www.phpmyadmin.net/](http://www.phpmyadmin.net/)

-- Host: 127.0.0.1

-- Generation Time: Jan 20, 2021 at 06:31 AM

-- Server version: 10.4.11-MariaDB

-- PHP Version: 7.2.29

SET SQL\_MODE = "NO\_AUTO\_VALUE\_ON\_ZERO"; START TRANSACTION;

SET time\_zone = "+00:00";

/\*!40101 SET @OLD\_CHARACTER\_SET\_CLIENT=@@CHARACTER\_SET\_CLIENT \*/;

/\*!40101 SET @OLD\_CHARACTER\_SET\_RESULTS=@@CHARACTER\_SET\_RESULTS \*/;

/\*!40101 SET @OLD\_COLLATION\_CONNECTION=@@COLLATION\_CONNECTION \*/;

/\*!40101 SET NAMES utf8mb4 \*/;

-- Database: `farmers`

-- Table structure for table `addagroproducts` CREATE TABLE `addagroproducts` (

`username` varchar (50) NOT NULL,

`email` varchar (50) NOT NULL,

`pid` int (11) NOT NULL,

`productname` varchar (100) NOT NULL,

`productdesc` text NOT NULL,

`price` int (100) NOT NULL

) ENGINE=InnoDB DEFAULT CHARSET=utf8mb4;

-- Dumping data for table `addagroproducts`

INSERT INTO `addagroproducts` (`username`, `email`, `pid`, `productname`, `productdesc`, `price`) VALUES

('test', ['test@gmail.com',](mailto:%27test@gmail.com) 1, 'GIRIJA CAULIFLOWER', ' Tips for Growing Cauliflower. Well drained medium loam and or sandy loam soils are suitable.', 520),

('test', ['test@gmail.com',](mailto:%27test@gmail.com) 2, 'COTTON', 'Cotton is a soft, fluffy staple fiber that grows in a boll, around the seeds of the cotton ', 563),

-- Table structure for table `farming`

CREATE TABLE `farming` (

`fid` int (11) NOT NULL,

`farmingtype` varchar (200) NOT NULL

) ENGINE=InnoDB DEFAULT CHARSET=utf8mb4;

-- Dumping data for table `farming`

INSERT INTO `farming` (`fid`, `farmingtype`) VALUES (1, 'Seed Farming'),

(2, 'coccon'),

(3, 'silk');

-- Table structure for table `register` CREATE TABLE `register` (

`rid` int (11) NOT NULL,

`farmername` varchar (50) NOT NULL,

`adharnumber` varchar (20) NOT NULL,

`age` int (100) NOT NULL,

`gender` varchar (50) NOT NULL,

`phonenumber` varchar (12) NOT NULL,

`address` varchar (50) NOT NULL,

`farming` varchar (50) NOT NULL

) ENGINE=InnoDB DEFAULT CHARSET=utf8mb4;

-- Triggers `register` DELIMITER $$

CREATE TRIGGER `deletion` BEFORE DELETE ON `register` FOR EACH ROW INSERT INTO trig VALUES (null,OLD.rid,'FARMER DELETED',NOW())

$$ DELIMITER; DELIMITER $$

CREATE TRIGGER `insertion` AFTER INSERT ON `register` FOR EACH ROW INSERT INTO trig VALUES (null,NEW.rid,'Farmer Inserted',NOW())

$$ DELIMITEM; DELIMITER $$

CREATE TRIGGER `updation` AFTER UPDATE ON `register` FOR EACH ROW INSERT INTO trig VALUES (null,NEW.rid,'FARMER UPDATED',NOW())

$$ DELIMITER;

-- Table structure for table `test` CREATE TABLE `test` (

`id` int (11) NOT NULL,

`name` varchar (50) NOT NULL

) ENGINE=InnoDB DEFAULT CHARSET=utf8mb4;

-- Dumping data for table `test`

INSERT INTO `test` (`id`, `name`) VALUES (1, 'harshith');

-- Table structure for table `trig` CREATE TABLE `trig` (

`id` int (11) NOT NULL,

`fid` varchar (50) NOT NULL,

`action` varchar (50) NOT NULL,

`timestamp` datetime NOT NULL

) ENGINE=InnoDB DEFAULT CHARSET=utf8mb4;

-- Dumping data for table `trig`

INSERT INTO `trig` (`id`, `fid`, `action`, `timestamp`) VALUES (1, '2', 'FARMER UPDATED', '2024-05-19 23:04:44'),

(2, '2', 'FARMER DELETED', '2024-05-19 23:04:58'),

CREATE TABLE `user` (

`id` int (11) NOT NULL,

`username` varchar (50) NOT NULL,

`email` varchar (50) NOT NULL,

`password` varchar (500) NOT NULL

) ENGINE=InnoDB DEFAULT CHARSET=utf8mb4;

-- Dumping data for table `user`

INSERT INTO `user` (`id`, `username`, `email`, `password`) VALUES (5,'arkpro’, ‘arkpro@gmail.com','pbkdf2: sha256:150000$TfhDWqOr$d4cf40');

-- Indexes for dumped tables

-- Indexes for table `addagroproducts` ALTER TABLE `addagroproducts` ADD PRIMARY KEY (`pid`);

-- Indexes for table `farming` ALTER TABLE `farming` ADD PRIMARY KEY (`fid`);

-- Indexes for table `register` ALTER TABLE `register` ADD PRIMARY KEY (`rid`);

-- Indexes for table `test` ALTER TABLE `test`

ADD PRIMARY KEY (`id`);

-- Indexes for table `trig` ALTER TABLE `trig`

ADD PRIMARY KEY (`id`);

-- Indexes for table `user` ALTER TABLE `user`

ADD PRIMARY KEY (`id`);

-- AUTO\_INCREMENT for dumped tables

-- AUTO\_INCREMENT for table `addagroproducts` ALTER TABLE `addagroproducts`

MODIFY `pid` int(11) NOT NULL AUTO\_INCREMENT, AUTO\_INCREMENT=4;

- AUTO\_INCREMENT for table `farming` ALTER TABLE `farming`

MODIFY `fid` int(11) NOT NULL AUTO\_INCREMENT, AUTO\_INCREMENT=4;

-- AUTO\_INCREMENT for table `register` ALTER TABLE `register`

MODIFY `rid` int(11) NOT NULL AUTO\_INCREMENT, AUTO\_INCREMENT=9;

-- AUTO\_INCREMENT for table `test` ALTER TABLE `test`

MODIFY `id` int(11) NOT NULL AUTO\_INCREMENT, AUTO\_INCREMENT=2;

-- AUTO\_INCREMENT for table `trig` ALTER TABLE `trig`

MODIFY `id` int(11) NOT NULL AUTO\_INCREMENT, AUTO\_INCREMENT=6;

-- AUTO\_INCREMENT for table `user` ALTER TABLE `user`

MODIFY `id` int(11) NOT NULL AUTO\_INCREMENT, AUTO\_INCREMENT=6; COMMIT;

/\*!40101 SET CHARACTER\_SET\_CLIENT=@OLD\_CHARACTER\_SET\_CLIENT \*/;

/\*!40101 SET CHARACTER\_SET\_RESULTS=@OLD\_CHARACTER\_SET\_RESULTS \*/;

/\*!40101 SET COLLATION\_CONNECTION=@OLD\_COLLATION\_CONNECTION \*/;

**Triggers.html:**

{% extends 'base.html' %}

{% block title %} Triggers

{% endblock title %}

{% block body %}

<h3 class="text-center"><span>Farmers Triggers Records</span> </h3>

{% with messages=get\_flashed\_messages(with\_categories=true) %}

{% if messages %}

{% for category, message in messages %}

<div class="alert alert-{{category}} alert-dismissible fade show" role="alert">

{{message}} </div>

{% endfor %} {% endif %}

{% endwith %} <br>

<div class="container mt-4">

<table class="table">

<thead class="thead-light"><tr>

<th scope="col">FARMER ID</th> <th scope="col">ACTION</th>

<th scope="col">TIMESTAMP</th></tr> </thead> <tbody>

{% for post in query %} <tr>

<td>{{post.fid}} </td> <td>{{post.action}}</td> <td>{{post.timestamp}}</td></tr>

{% endfor %}

</tbody></table></div>

{% endblock body %}

**agroproducts.html:**

{% extends 'base.html' %}{% block title %} Agro Products

{% endblock title %} {% block body %}

<h3 class="text-center"><span>Agro Products</span> </h3>

{% with messages=get\_flashed\_messages(with\_categories=true) %}

{% if messages %} {% for category, message in messages %}

<div class="alert alert-{{category}} alert-dismissible fade show" role="alert">

{{message}} </div>

{% endfor %} {% endif %} {% endwith %}<br>

<div class="container mt-3"><div class="row">

{% for p in query %} <div class="col-sm-4"><div class="card">

<div class="card-body"><b><h5 class="card-title">{{p. productname}}</h5></b>

<b>Price : {{p.price}}</b><hr><p class="card-text">{{p.productdesc}}</p>

<p>Owner:{{p.username}}</p><p>Email:{{p.email}}</p>

<ahref="https://mail.google.com/mail/?view=cm&fs=1&tf=1&to={{p.email}}"target="\_blank" class="btn btn- success ">Purchase</a> </div> </div></div>

{% endfor %} </div></div>

{% endblock body %}

**auth.html:**

<!DOCTYPE html>

<html lang="en">

<head>

<meta charset="utf-8">

<meta content="width=device-width, initial-scale=1.0" name="viewport">

<title> {% block title %}

{% endblock title %} </title>

<meta content="" name="description">

<meta content="" name="keywords">

{% block style %}

{%endblockstyle%}

<linkhref="https://fonts.googleapis.com/css?family=Open+Sans:300,300i,400,400i,700,700i|Raleway:300,400,500

,700,800" rel="stylesheet">

<! -- Vendor CSS Files -->

<link href="static/assets/vendor/bootstrap/css/bootstrap.min.css" rel="stylesheet">

<link href="static/assets/vendor/font-awesome/css/font-awesome.min.css" rel="stylesheet">

<link href="static/assets/vendor/owl.carousel/assets/owl.carousel.min.css" rel="stylesheet">

<link href="static/assets/vendor/aos/aos.css" rel="stylesheet">

<link href="static/assets/css/style.css" rel="stylesheet">

</head><body>

<header id="header">

<div class="container">

<div id="logo" class="pull-left">

<a href="/" class="scrollto">Farm Management</a></div></div>

</header><! -- End Header -->

<section id="intro">

<div class="intro-container" data-aos="zoom-in" data-aos-delay="100">

{% block content %}

{% endblock content %} </div>

</section><! -- End Intro Section -->

<div class="main">

<footer id="footer">

<div class="footer-top"><div class="container"></div><div class="container"><div class="credits"><br> Developed by <a href="/">Vrishi and Shruti</a>

</div></div></footer><! -- End Footer -->

<a href="#" class="back-to-top"><i class="fa fa-angle-up"></i></a>

<script src="static/assets/vendor/jquery/jquery.min.js"></script>

<script src="static/assets/vendor/bootstrap/js/bootstrap.bundle.min.js"></script>

<script src="static/assets/vendor/jquery.easing/jquery.easing.min.js"></script>

<script src="static/assets/vendor/php-email-form/validate.js"></script>

<script src="static/assets/vendor/venobox/venobox.min.js"></script>

<script src="static/assets/vendor/owl.carousel/owl.carousel.min.js"></script>

<script src="static/assets/vendor/superfish/superfish.min.js"></script>

<script src="static/assets/vendor/hoverIntent/hoverIntent.js"></script>

<script src="static/assets/vendor/aos/aos.js"></script>

script src="static/assets/js/main.js"></script></body></html>

**base.html:**

<!DOCTYPE html>

<html lang="en">

<head> <meta charset="utf-8">

<meta content="width=device-width, initial-scale=1.0" name="viewport">

<title> {% block title %}

{% endblock title %} </title>

<meta content="" name="description">

<meta content="" name="keywords">

{% block style %}

{%endblockstyle%}

<linkhref="https://fonts.googleapis.com/css?family=Open+Sans:300,300i,400,400i,700,700i|Raleway:300,400,500

,700,800" rel="stylesheet">

<! -- Vendor CSS Files -->

<link href="static/assets/vendor/bootstrap/css/bootstrap.min.css" rel="stylesheet">

<link href="static/assets/vendor/venobox/venobox.css" rel="stylesheet">

<link href="static/assets/vendor/font-awesome/css/font-awesome.min.css" rel="stylesheet">

<link href="static/assets/vendor/owl.carousel/assets/owl.carousel.min.css" rel="stylesheet">

<link href="static/assets/vendor/aos/aos.css" rel="stylesheet">

<!-- Template Main CSS File -->

<link href="static/assets/css/style.css" rel="stylesheet"></head>

<body>

<header id="header">

<div class="container">

<div id="logo" class="pull-left">

<a href="/" class="scrollto">F.A. S</a></div>

<nav id="nav-menu-container">

<ul class="nav-menu">

<li class="{% block home %}

{% endblock home %}"><a href="/">Home</a></li>

<li><a href="/register">Farmer Register</a></li>

<li><a href="/addfarming">Add Farming</a></li>

<li><a href="/farmerdetails">Farmer Details</a></li>

<li><a href="/agroproducts">Agro Products</a></li>

<li><a href="/triggers">Records</a></li>

{% if current\_user.is\_authenticated %}

<li class="buy-tickets"><a href="">Welcome {{current\_user. username}} </a></li>

<li class="buy-tickets"><a href="/logout">Logout</a></li>

{% else %} <li class="buy-tickets"><a href="/signup">Signin</a></li> {% endif %}

</ul> </nav><! -- #nav-menu-container --></div> </header>

<section id="intro">

<div class="intro-container" data-aos="zoom-in" data-aos-delay="100">

<h1 class="mb-4 pb-0">SELL AND BUY AGRO PRODUCTS </span> </h1>

<a href="/agroproducts" class="about-btn scrollto">AGRO PRODUCTS</a></div>

</section><! -- End Intro Section -->

<main id="main">

{% block body %}

{% with messages=get\_flashed\_messages(with\_categories=true) %}

{% if messages %}

{% for category, message in messages %}

<div class="alert alert-{{category}} alert-dismissible fade show" role="alert">

{{message}}

</div>

{% endfor %} {% endif %}

{% endwith %} {% endblock body %}

<a href="#" class="back-to-top"><i class="fa fa-angle-up"></i></a>

<!-- Vendor JS Files -->

<script src="static/assets/vendor/jquery/jquery.min.js"></script>

<script src="static/assets/vendor/bootstrap/js/bootstrap.bundle.min.js"></script>

<script src="static/assets/vendor/jquery.easing/jquery.easing.min.js"></script>

<script src="static/assets/vendor/php-email-form/validate.js"></script>

<script src="static/assets/vendor/venobox/venobox.min.js"></script>

<script src="static/assets/vendor/owl.carousel/owl.carousel.min.js"></script>

<script src="static/assets/vendor/superfish/superfish.min.js"></script>

<script src="static/assets/vendor/hoverIntent/hoverIntent.js"></script>

<script src="static/assets/vendor/aos/aos.js"></script>

<!-- Template Main JS File --><script src="static/assets/js/main.js"></script></body></html>

**edit.html:**

<!doctype html>

<html lang="en">

<head> <meta charset="utf-8">

<meta name="viewport" content="width=device-width, initial-scale=1, shrink-to-fit=no">

<!--BootstrapCSS-->

<linkrel="stylesheet"href="[https://cdn.jsdelivr.net/npm/bootstrap@4.5.3/dist/css/bootstrap.min.css](https://cdn.jsdelivr.net/npm/bootstrap%404.5.3/dist/css/bootstrap.min.css)"integrity="sha3 84TX8t27EcRE3e/ihU7zmQxVncDAy5uIKz4rEkgIXeMed4M0jlfIDPvg6uqKI2xXr2" crossorigin="anonymous">

<title>Edit</title>

</head><body class="bg-success"> <h3 class="text-center"><span>Edit Farmer Details</span> </h3>

{% with messages=get\_flashed\_messages(with\_categories=true) %}

{% if messages %} {% for category, message in messages %}

<div class="alert alert-{{category}} alert-dismissible fade show" role="alert">

{{message}}</div>

{% endfor %}{% endif %} {% endwith %}<br>

<div class="container"> <div class="row"><div class="col-md-4"></div>

<div class="col-md-4"><form action="/edit/{{posts.rid}}" method="post">

<div class="form-group"> <label for="rollno">Farmer Name</label>

<input type="text" class="form-control" name="farmername" id="farmername" value={{posts.farmername}} required></div><br>

<div class="form-group"> <label for="adharnumber">Adhar Number</label>

<input type="number" class="form-control" name="adharnumber" id="adharnumber" value={{posts.adharnumber}} required></div><br>

<div class="form-group"><label for="age">Age</label>

<input type="number" class="form-control" name="age" id="age" value={{posts.age}} required></div><br>

<div class="form-group">

<select class="form-control" id="gender" name="gender" required>

<option selected>{{posts.gender}} </option>

<option value="male">Male</option>

<option value="female">Female</option> </select></div><br>

<div class="form-group">

<label for="num">Phone Number</label>

<input type="number" class="form-control" name="phonenumber" id="phonenumber" value={{posts.phonenumber}} required>

</div><br><div class="form-group">

<label for="address">Address</label>

<input class="form-control" name="address" id="address" value={{posts.address}} required/>

</div><br><div class="form-group">

<select class="form-control" id="farmingtype" name="farmingtype" required>

<option selected>{{posts.farming}}</option>

{% for d in farming %}

<option value="{{d.farmingtype}}">{{d.farmingtype}}</option>

{% endfor %} </select></div><br>

<button type="submit" class="btn btn-light btn-sm btn-block">Submit Record</button></form>

<br><br></div><div class="col-md-4"></div></div></div></div>

<!-- Optional JavaScript; choose one of the two! -->

<!Option1:jQueryandBootstrapBundle(includesPopper)<scriptsrc="https://code.jquery.com/jquery3.5.1.slim.min.js "integrity="sha384DfXdz2htPH0lsSSs5nCTpuj/zy4C+OGpamoFVy38MVBnE+IbbVYUew+OrCXaRkfj" crossorigin="anonymous"></script>

<scriptsrc="[https://cdn.jsdelivr.net/npm/bootstrap@4.5.3/dist/js/bootstrap.bundle.min.js](https://cdn.jsdelivr.net/npm/bootstrap%404.5.3/dist/js/bootstrap.bundle.min.js)"integrity="sha384- ho+j7jyWK8fNQe+A12Hb8AhRq26LrZ/JpcUGGOn+Y7RsweNrtN/tE3MoK7ZeZDyx" crossorigin="anonymous"></script>

<!--Option2:jQuery,Popper.js,andBootstrapJS

<scriptsrc="https://code.jquery.com/jquery3.5.1.slim.min.js"integrity="sha384DfXdz2htPH0lsSSs5nCTpuj/zy4C+ OGpamoFVy38MVBnE+IbbVYUew+OrCXaRkfj" crossorigin="anonymous"></script>

<script src="[https://cdn.jsdelivr.net/npm/popper.js@1.16.1/dist/umd/popper.min.js](https://cdn.jsdelivr.net/npm/popper.js%401.16.1/dist/umd/popper.min.js)" integrity="sha384- 9/reFTGAW83EW2RDu2S0VKaIzap3H66lZH81PoYlFhbGU+6BZp6G7niu735Sk7lN"

crossorigin="anonymous"></script>

<script src="[https://cdn.jsdelivr.net/npm/bootstrap@4.5.3/dist/js/bootstrap.min.js](https://cdn.jsdelivr.net/npm/bootstrap%404.5.3/dist/js/bootstrap.min.js)" integrity="sha384- w1Q4orYjBQndcko6MimVbzY0tgp4pWB4lZ7lr30WKz0vr/aWKhXdBNmNb5D92v7s" crossorigin="anonymous"></script> </body>

</html>

**farmer.html:**

{% extends 'base.html' %}{% block title %} Register Farmers Details

{% endblock title %}{% block body %}

<h3 class="text-center"><span>Register Farmers Details</span> </h3>

{% with messages=get\_flashed\_messages(with\_categories=true) %}

{% if messages %}

{% for category, message in messages %}

<div class="alert alert-{{category}} alert-dismissible fade show" role="alert">

{{message}}</div>

{% endfor % {% endif %}

{% endwith %}<br>

<div class="container">

<div class="row"><div class="col-md-4"></div>

<div class="col-md-4"><form action="/register" method="post">

<div class="form-group"><label for="rollno">Farmer Name</label>

<input type="text" class="form-control" name="farmername" id="farmername" required>

</div><br><div class="form-group">

<label for="adharnumber">Adhar Number</label>

<input type="number" class="form-control" name="adharnumber" id="adharnumber" required></div><br>

<div class="form-group"><label for="age">Age</label>

<input type="number" class="form-control" name="age" id="age" required></div><br><div class="form-group">

<select class="form-control" id="gender" name="gender" required>

<option selected>Select Gender</option>

<option value="male">Male</option>

<option value="female">Female</option></select></div><br>

<div class="form-group">

<label for="num">Phone Number</label>

<input type="number" class="form-control" name="phonenumber" id="phonenumber" required></div><br>

<div class="form-group"><label for="address">Address</label>

<textarea class="form-control" name="address" id="address" required></textarea>

</div><br><div class="form-group">

<select class="form-control" id="farmingtype" name="farmingtype" required>

<option selected>Select Farming</option>

{% for d in farming %}

<option value="{{d. farmingtype}}">{{d.farmingtype}}</option>

{% endfor %} </select></div><br>

<button type="submit" class="btn btn-success btn-block">Save Records</button>

</form><br><br></div><div class="col-md-4"></div></div></div>

{% endblock body %}

**farmerdetails.html:**

{% extends 'base.html' %}{% block title %} Farmer Details

{% endblock title %}{% block body %}

<h3 class="text-center"><span>Farmer Details</span> </h3>

{% with messages=get\_flashed\_messages(with\_categories=true) %}

{% if messages %}

{% for category, message in messages %}

<div class="alert alert-{{category}} alert-dismissible fade show" role="alert"> {{message}} </div>

{% endfor %}{% endif %}{% endwith %}<br>

<div class="container mt-3"> <table class="table">

<thead class="thead-light"><tr>

<th scope="col">RID</th> <th scope="col">FARMER NAME</th>

<th scope="col">ADHAR NUMBER</th> <th scope="col">AGE</th>

<th scope="col">GENDER</th> <th scope="col">PHONE NUMBER</th>

<th scope="col">ADDRESS</th> <th scope="col">FARMING</th>

<th scope="col">EDIT</th> <th scope="col">DELETE</th>

<th scope="col">ADD AGRO PRODUCT</th></tr> </thead> <tbody>

{% for post in query %} <tr>

<th scope="row">{{post.rid}}</th>

<td> {{post. farmer name}} </td>

<td> {{post. adharnumber}} </td> <td>{{post. Age}} </td>

<td> {{post. gender}} </td> <td>{{post. phonenumber}}</td>

<td> {{post. address}} </td> <td>{{post.farming}}</td>

<td><a href="/edit/{{post.rid}}"><button class="btn btn-success">Edit </button> </a> </td>

<td><a href="/delete/{{post.rid}}"><button onclick="return confirm ('Are you sure to Delete data');" class="btn btn-success">Delete </button> </a> </td>

<td><a href="/addagroproduct"><button class="btn btn-success">ADD </button> </a> </td></tr>

{% endfor %} </tbody></table></div>

{% endblock body %}

**farming.html:**

{% extends 'base.html' %}{% block title %} Add Farming

{% endblock title %}{% block body %}

<h3 class="text-center bg-success text-white"><span>Add Farming</span> </h3>

{% with messages=get\_flashed\_messages(with\_categories=true) %}

{% if messages %} {% for category, message in messages %}

<div class="alert alert-{{category}} alert-dismissible fade show" role="alert"> {{message}}</div>

{% endfor %} {% endif %}

{% endwith %} <br><div class="container"><div class="row">

<div class="col-md-4"></div><div class="col-md-4">

<form action="/addfarming" method="post"> <div class="form-group">

<label for="dept">Enter Farming Type</label>

<input type="text" class="form-control" name="farming" id="farming"></div><br>

<button type="submit" class="btn btn-success btn-sm btn-block">Add Farming</button>

</form><br><br></div> <div class="col-md-4"></div></div></div>

{% endblock body %}

**Stored Procedure:**

Routine name: proc Type: procedure

Definition: Select \* from register;

**Triggers**:

It is the special kind of stored procedure that automatically executes when an event occurs in the database. Triggers used:

1. Trigger name: on insert Table: register Time: after Event: INSERT INTO trig VALUES (null, NEW.rid, 'Farmer Inserted’, NOW ())
2. Trigger name: on delete Table: register Time: after Event: delete Definition: INSERT INTO trig VALUES (null, OLD. Rid, 'FARMER DELETED’, NOW ())
3. Trigger name: on update Table: register Time: after Event: update Definition: INSERT INTO trig VALUES (null, NEW.rid,'FARMER UPDATED’, NOW ())

# REFERENCES

1. Soko Manav Singhal, Kshitij Verma, Anupam Shukla, “Krishi Ville - Android based solution for Indian agriculture”. 2011 Fifth IEEE International Conference on Advanced Telecommunication Systems and Networks (ANTS), 18-21 Dec. 2011, Bangalore, India.
2. R. Sneha Iyer, R. Shruthi, K. Shruthhi and R. Madhumathi, "Spry Farm: A Portal for Connecting Farmers and End Users," 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2021, pp. 429433, doi:10.1109/ICACCS51430.2021.9441815.
3. Shankar M. Patil, Monika Jadhav, Vishakha Jagtap, “Android Application for Farmers”, International Research Journal of Engineering and Technology, volume 6, issue 4, 2019, 4200-4202p.
4. Abishek A. G., Bharathwaj M., Bhagyalakshmi L. “Agriculture Marketing Using Web and Mobile Based Technologies”, 2016 IEEE International Conference on Technological Innovations in ICT For Agriculture and Rural Development (TIAR 2016).
5. D. Tilman C. Balzer J. Hill B.L. Befort Global food demand and the sustainable intensification of agriculture Proceedings of the National Academy of Sciences 108 50 2011 20260 20264
6. Babcock B 2013 *Cutting Waste in the Crop Insurance Program* ed N Bruzelius (Washington, DC: EnvironmentalWorkingGroup) ( [http://cdn.ewg.org/sites/default/files/u118/2013%20Cutting%20Crop%20Insurance](http://cdn.ewg.org/sites/default/files/u118/2013%20Cutting%20Crop%20Insurance%20Waste_.pdf?_ga=1.110206349.96985284.1437058644)

[%20Waste\_.pdf?\_ga=1.110206349.96985284.1437058644](http://cdn.ewg.org/sites/default/files/u118/2013%20Cutting%20Crop%20Insurance%20Waste_.pdf?_ga=1.110206349.96985284.1437058644))

1. Md Iqbal, Vimal Kumar and Vijay Kumar Sharma. Krishi Portal: Web Based Farmer Help Assistance. International Journal of Advanced Science and Technology Vol. 29, No. 6, (2020), pp. 4783 – 4786
2. Agriculture marketing using web and mobile based technologies. 2016 IEEE Technological Innovations in ICT for Agriculture and Rural Development. doi:10.1109/tiar.2016.7801211
3. Vishi Purushottam Paliwal et al, “Design of Web Portal for ETrading for Farmers”, International Journal on Future Revolution in Computer Science and Communication Engineering, vol. 4, pp. 220-222, 2018.
4. Specification for security management systems for the supply chain, ISO 28000- 2007,2007.[Online].Available:<http://www.iso.org/iso/catalogue_detail?csnumber=446> 41 C. Speier, J. M. Whipple, D. J. Closs, and M. D. Voss, “Global supply chain design considerations: Mitigating product safety and security risks,” J. Oper. Manage., vol. 29,

pp. 721 736, 2011.

1. C. Speier, J. M. Whipple, D. J. Closs, and M. D. Voss, “Global supply chain design considerations: Mitigating product safety and security risks,” J. Oper. Manage., vol. 29,

pp. 721 736, 2011.

1. Shital Chaudhari, Vaishnavi Mhatre, Pooja Patil, Sandeep Chavan, “Smart Farm Application: A Modern Farming Technique Using Android Application”, IJRET, Feb 2018.
2. https://ieeexplore.ieee.org/document/9182969 A Study of Blockchain Technology in Farmer's Portal Sheetal Bhagwat et al, “Survey Paper on E-Mandi A Market Exchanging Between Farmers and End-user”, International Research Journal of Engineering and Technology, vol. 6, 2019.
3. https://prepinsta.com/software-engineering/iterative-waterfall-model/
4. <https://internetcomputer.org/>

Farming Portal: Web Based Agriculture Assistance Services

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***Abstract*—: Agriculture forms the backbone of India's economy, with farmers serving as the primary providers of sustenance for the population. However, the traditional supply chain in the agricultural sector, characterized by the involvement of numerous intermediaries, often leaves the cultivators marginalized, while middlemen reap significant profits. Recognizing the transformative potential of science in addressing this issue, this review paper proposes the integration of direct-to-consumer agricultural platforms into the Indian Agronomy landscape. In the contemporary era dominated by technological advancements, the widespread use of smartphones and digital platforms has revolutionized various aspects of daily life. Building upon this trend, the objective of this paper is to explore the feasibility and impact of leveraging equipment to facilitate direct transactions between tillers and consumers. The paper underscores the transformative potential of innovation in empowering farmers and reshaping the agricultural landscape in India. By fostering direct connections between producers and consumers, these platforms have the capacity to not only improve grower’s incomes but also enhance food security, promote sustainable agriculture practices, and strengthen rural economies. Through continued innovation and collaboration, the realization of a more inclusive and equitable agricultural system is within reach. Information and Communication Technologies (ICTs) are playing pivotal roles across various technical domains including education, banking, healthcare, e- commerce, and numerous others. This paper describes a web- based system - "Farming Portal" - which will help agrarians obtain information about various yields, crop diseases, its prices, and government schemes for the cultivators.**

***Keywords—Agriculture, Customer, Farmers, Middlemen.***

1. Introduction

In India, Agriculture is a crucial part. A Farmer is a person who is engaged in agricultural activities [1]. Agriculturists play a crucial role in our society as they are the primary providers of the food we consume. Since every person needs proper food for their sustenance, cultivators are a necessity in society. However, nowadays, they don't receive their deserved income for their hard work due to the involvement of intermediaries in the sector who take all the profit. As we embrace the modern era of machinery, we discover numerous engineering solutions that prove highly advantageous for societal advancements. This is the age of advancements, where people rely on smartphones to accomplish their daily tasks such as shopping, paying bills, managing work, and

much more. The objective of this project is to integrate its features into people's lives, enabling them to purchase food directly from the farm, ensuring that profits reach the farmers directly. In India, the prevailing supply chain for farm products creates excessive intermediaries, leaving the agrarians impoverished while intermediaries amass profits [2], perpetuating their wealth. So, in to break that supply chain of indirect sales, we can make use of this toolset [3] so that the farmer can be connected directly to the customer, and the selling can be done accordingly.

1. LITERATURE SURVEY

To develop this system, we studied some previous papers. The agricultural sector, the backbone of the global economy, has been undergoing significant transformations in recent years due to the integration of digital technologies and web- based services [4]. This literature survey provides an overview of key studies, research, and trends related to cultivating 02 assistance web services and removing dealers and negotiators in agriculture.

1. *Historical Role of Mediators in Agriculture*

Historically, intermediaries have played a vital role in connecting the planters with markets and resources. Studies such as Williamson (1979) emphasized the importance of go- betweens in reducing transaction costs. However, various scholars have also highlighted the exploitative practices and inefficiencies associated with middlemen, as discussed in the work of Reardon et al. (1992) and Tilman et al [5].

1. *Benefits of Removing the Intermediaries*

Several studies have highlighted the advantages of removing go-between from the agricultural supply chain. Swinnen (2007) argues that direct farmer-buyer interactions can lead to higher profits for ranchers and more transparent pricing. Additionally, Babcock [6] and Clemens (2004) found that eliminating intermediaries can reduce transaction costs.

1. *Challenges and Concerns*

While the idea of removing brokers is promising, it also raises concerns. Research conducted by the World Bank (2015) underscores the challenge faced by farmers in developing countries, who often lack the essential digital literacy and

internet access required to leverage web-based services. Concerns regarding privacy and data security have been articulated by scholars like Smith et al. (2018).

1. *Case Studies of Successful Implementation*

Numerous case studies showcase successful implementations of web-based Cultivating assistance services. The case of AgroStar in India, described by Kumar and Qureshi (2018), demonstrates how a mobile app [7] can connect growers with agricultural inputs and advisory services. Similarly, the FarmLogs platform in the United States, highlighted in Lowenberg-DeBoer and Erickson (2018), provides insights into the benefits of data-driven farm management [8]. "Design of Web Portal for E-Trading for Farmers" by Vishi Purushottam Paliwal et al. describes the design and development of a web portal aimed at facilitating e-trading between producers and buyers. The authors of this article [9] also highlighted the importance of educating farmers about e- trading and providing them with the necessary training and support.

1. *Future Prospects and Policy Considerations*

The future of web-based farming assistance services is a topic of ongoing research. Scholars like Hobbs (2018) discuss the role of artificial intelligence and machine learning in shaping the future of agriculture. Policy and regulatory considerations are also significant, as highlighted by Marette and Messéan (2017). The article "A Study of Blockchain Technology in Farmer's Portal," published on IEEE Xplore, delves into the transformative potential of blockchain techniques within the realm of farmer's portals [10]. The authors propose a blockchain-based farmer's portal architecture that integrates components such as smart contracts, digital identities, and data storage. The article also discusses the potential benefits of this architecture, such as increased efficiency, reduced costs, and improved data security and privacy.

1. PROPOSED SYSTEM

The system proposed by us aims to streamline the marketing of agricultural products for agriculturists, benefiting both farmers and buyers alike. The system is developed as a web platform using HTML, CSS, JavaScript, PHP, and MySQL, featuring interfaces tailored for both large and small screens. Both the ranchers and end user need to log in to the system by providing all necessary details to access its features. This system is a website as well as a mobile application. Cultivators can use the system directly by entering the URL of our website or just by opening the tool. At this stage, users will receive fundamental husbandry-related information. If they wish to engage in selling or purchasing, such as rural workers intending to sell their produce, registration through the provided form and subsequent login are mandatory. 03 Similarly, for purchasing, registration and login procedures are also required. Apart from farmers, two types of people can also benefit from this system: a) Consumer b) Supplier The information provided by the farmer regarding their products will be stored in the database. All details of the farmer, including their product, price, location, and contact number, will be showcased to the end user during the purchase process. Additionally, this system offers multi-

language support to enhance user-friendliness and accessibility across various local languages.

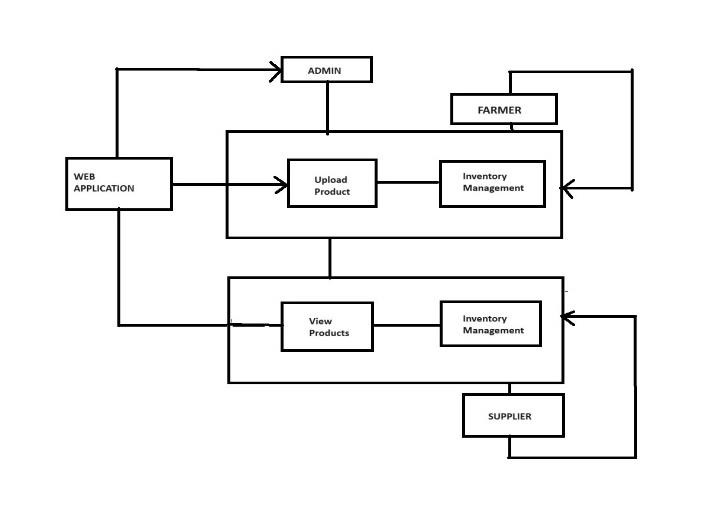


Fig. 1. The Block Diagram of the Application for buying and selling of the product

In Figure 1. the block diagram of the proposed system is explained. The system involves three actors: admin, farmer, and consumer. Upon successful registration, both the farmer and the buyer will receive a username and password. To input product information, the farmer must log in with the correct credentials. The customer can select any product available that they need and place an order. All the current news and updates related to various products or agricultural fairs going on would be displayed on the portal. Additionally, the portal will provide a list of current market rates for specific products. Thus, this portal will serve as a benchmark for all producers to enhance their profits, consequently leading to an uplift in our country's economy.

1. METHODOLOGY
2. *The Customer/User:*

Customer module contains the following:

* + Customer details
  + Post Advertisement
  + Crop Received
  + Make Payments

1. *The Farmer:*

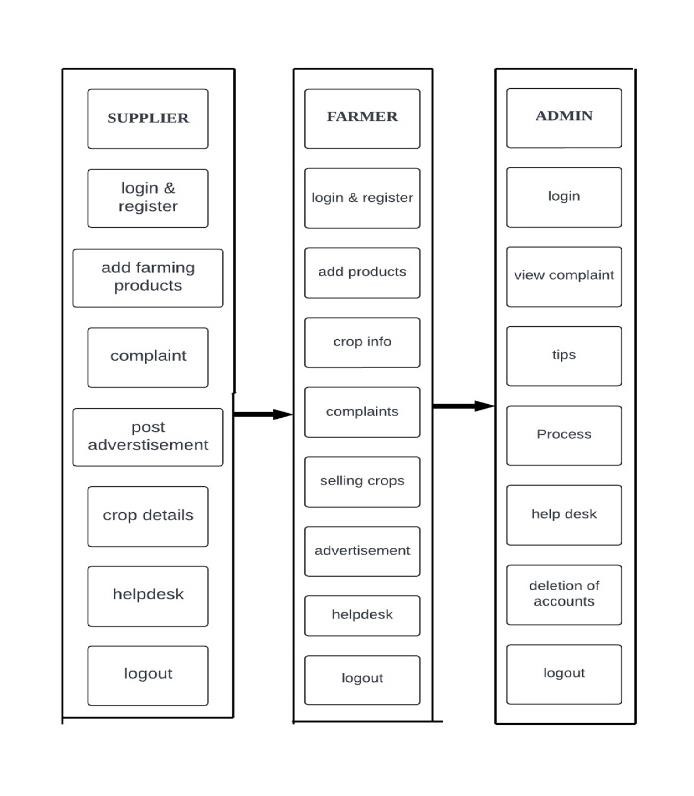
Farmer module contains the following:

* + Complaint Page
  + Complaint Status
  + Tilling Tips
  + Yield Advertisement Details
  + Sell Produce
  + Sell Harvest Details
  + Edit Farmer Details

1. *Admin:*

Admin module contains:

* + View Complaints.
  + Horticulture Tip
    - Farmers also have the option to post complaints, which will be addressed by the administration.



*B. Disadvantages of Agriculture Assistance Services*

* The growers in remote or underserved areas may have limited internet access, hindering their ability to use the system effectively.
* Rural workers with low literacy levels or who speak languages not supported by the software may struggle to use it effectively.
* The cost of developing, deploying, and maintaining such a system, including hardware, software, and support, may be a barrier to widespread adoption.
* The digital divide can exacerbate disparities, as growers with limited access to equipment may be left behind.
* Too much data without proper guidance can lead to fraud in some cases, also making it challenging to extract actionable insights.

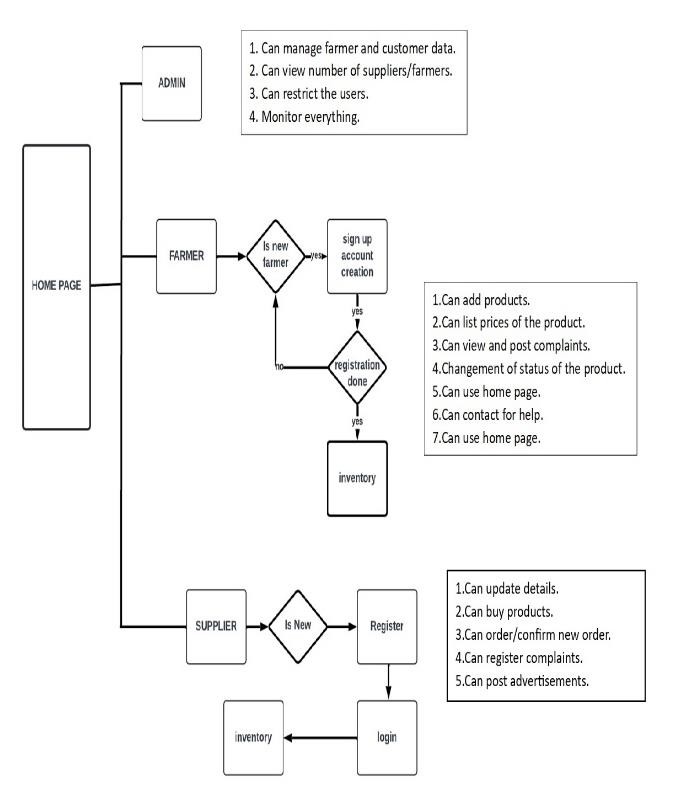
Fig. 2. Component Description of the Platform containing three modules.

1. MODELLING AND ANALYSIS
2. *Description*

Agriculture Products -> Sale/Purchase with End Customer from Farmer Modules

* + Admin - Account Control
  + Farmer-Products/Stock Add/Update/Delete, Customer Reports.
  + Customer - Profile Maintain, Order Details

1. *Tools/System*
   * Programming Language: MySQL
   * Back End Framework: PHP
   * Front End Framework: HTML, CSS, JavaScript
   * Future Scope: AI/ML
2. SPECIFICATIONS



*A. Advantages of Farming Assistance Services*

* The growers can access a wealth of information on various subjects at their fingertips. Informed decisions can result in increased productivity and profitability.
* The cultivators can connect with potential buyers, expanding their market reach and increasing sales opportunities, which can lead to better income and market stability.
* The cultivators can advertise their crops to showcase their products to potential suppliers.
* The producers can sell their products directly to the supplier without the involvement of the mediators.

Fig. 3. Components of the System with its working.

1. CONCLUSION

The proposed system heralds a transformative era in Indian agriculture, challenging the entrenched dominance of middlemen and fostering direct engagement between producers and consumers. This innovative platform, fortified by cutting-edge technologies empowers the agriculturists by ensuring equitable profits and endows consumers with transparent pricing mechanisms. Amidst its promise, the portal confronts formidable hurdles. Authentication emerges as a pivotal challenge, demanding robust mechanisms to safeguard user data and ensure secure transactions. Moreover, the digital divide looms large, as disparities in digital literacy

and internet access threaten to marginalize certain cultivation communities. Nevertheless, the "Farming Portal" stands as a beacon of hope, offering a pathway towards a more equitable, efficient, and resilient agricultural landscape. Through concerted efforts to surmount authentication challenges and bridge the digital gap, this pioneering platform holds the potential to revolutionize India's agricultural 05 paradigm, propelling the growers towards prosperity and bolstering food security for generations to come.

References

1. Manav Singhal, Kshitij Verma, Anupam Shukla, “Krishi Ville - Android-based solution for Indian agriculture”. 2011 Fifth IEEE International Conference on Advanced Telecommunication Systems and Networks (ANTS), 18-21 Dec. 2011, Bangalore, India.
2. R. Sneha Iyer, R. Shruthi, K. Shruthhi and R. Madhumathi, "Spry Farm: A Portal for Connecting Farmers and End Users," 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2021, pp. 429433, doi:10.1109/ICACCS51430.2021.9441815
3. Shankar M. Patil, Monika Jadhav, Vishakha Jagtap, “Android Application for Farmers”, International Research Journal of Engineering and Technology, volume 6, issue 4, 2019, 4200-4202p.
4. Abishek, A. G., Bharathwaj, M., & Bhagyalakshmi, L. (2016). Agriculture marketing using web and mobile-based technologies. 2016 IEEE Technological Innovations in ICT for Agriculture and Rural Development. (TIAR). doi:10.1109/tiar.2016.7801211
5. D. Tilman C. Balzer J. Hill B.L. Befort Global food demand and the sustainable intensification of agriculture Proceedings of the National Academy of Sciences 108 50 2011 20260 20264
6. Babcock B 2013 Cutting Waste in the Crop Insurance Program ed N Bruzelius (Washington, DC: Environmental Working Group)

[http://cdn.ewg.org/sites/default/files/u118/2013%20Cutting%20Crop](http://cdn.ewg.org/sites/default/files/u118/2013%20Cutting%20Crop%20Insurance%20Waste_.pdf?_ga=1.110206349.96985284.1437058644)

[%20Insurance%20Waste\_.pdf?\_ga=1.110206349.96985284.1437058](http://cdn.ewg.org/sites/default/files/u118/2013%20Cutting%20Crop%20Insurance%20Waste_.pdf?_ga=1.110206349.96985284.1437058644) [644](http://cdn.ewg.org/sites/default/files/u118/2013%20Cutting%20Crop%20Insurance%20Waste_.pdf?_ga=1.110206349.96985284.1437058644)

1. Md Iqbal, Vimal Kumar and Vijay Kumar Sharma. Krishi Portal: Web Based Farmer Help Assistance. International Journal of Advanced Science and Technology Vol. 29, No. 6, (2020), pp. 4783 – 4786
2. Agriculture marketing using web and mobile-based technologies. 2016 IEEE Technological Innovations in ICT for Agriculture and Rural Development. (TIAR).
3. Vishi Purushottam Paliwal et al, “Design of Web Portal for ETrading for Farmers”, International Journal on Future Revolution in Computer Science and Communication Engineering, vol. 4, pp. 220-222, 2018.
4. Specification for security management systems for the supply chain, ISO 28000-2007, 2007. [Online]. Available: <http://www.iso.org/iso/catalogue_detail?csnumber=44641>
5. C. Speier, J. M. Whipple, D. J. Closs, and M. D. Voss, “Global supply chain design considerations: Mitigating product safety and security risks,” J. Oper. Manage., vol. 29, pp. 721 736, 2011.
6. Shital Chaudhari, Vaishnavi Mhatre, Pooja Patil, Sandeep Chavan, “Smart Farm Application: A Modern Farming Technique Using Android Application”, IJRET, Feb 2018.
7. A Study of Blockchain Technology in Farmer's Portal Sheetal Bhagwat et al, “Survey Paper on E-Mandi A Market Exchanging Between Farmers and End-user”, International Research Journal of Engineering and Technology, vol. 6, 2019.
8. <https://ieeexplore.ieee.org/document/9182969>