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Chenlep Yakha Konyak
Assistant Professor, Computer Science and Engineering, School of Engineering and Technology (SET), Nagaland University, Dimapur, Nagaland, India

Corresponding Author:
Chenlep Yakha Konyak
Assistant Professor, Computer Science and Engineering, School of Engineering and Technology (SET), Nagaland University, Dimapur, Nagaland, India

Data-driven clustering techniques in evaluating pharmacy performance

Chenlep Yakha Konyak

Abstract
This study addresses the need for a more sophisticated analysis of pharmacy performance data to uncover hidden patterns, correlations, and operational inefficiencies over traditional pharmacy evaluation methods. Applying machine learning techniques, specifically K-Means clustering and Principal Component Analysis (PCA), to a dataset of 100,010 examples, the research examines key performance metrics such as sales revenue, prescription volume, medication adherence rate, and customer satisfaction scores. The experimental approach segments pharmacies into distinct groups using K-Means clustering and employs PCA for two-dimensional visualization. The findings reveal four unique clusters, each with different operational strengths and weaknesses, highlighting the importance of technology adoption, online services, and community engagement in driving pharmacy performance. The study concludes that machine learning techniques provide valuable insights and strategic guidance for healthcare stakeholders, suggesting that investments in technology and community-focused services can optimize pharmacy operations and enhance patient outcomes.

Keywords: Pharmacy performance, operational metrics, k-means, machine learning

1. Introduction

Pharmacy performance stands as a cornerstone within the healthcare ecosystem, wielding profound influence over medication adherence, patient satisfaction, and the overarching expenses of healthcare delivery. The efficient operation of pharmacies is critical for ensuring the timely delivery of medications, maintaining the quality of patient care, and optimizing healthcare costs. Historically, scrutinizing this performance has relied upon conventional methodologies rooted in descriptive statistics and regression models. These traditional approaches, while useful, often fall short of capturing the intricate and multifaceted nature of pharmacy operations (Taylor *et al*., 2019) [9].

The contemporary landscape, propelled by the emergence of big data and sophisticated machine learning methodologies (Balajee *et al*., 2019) [3], offers an unprecedented opportunity to delve deeper into the nuances of pharmacy performance. The advent of machine learning techniques allows for the processing and analysis (Yan *et al*., 2019) [2] of vast amounts of data, enabling the discovery of hidden patterns and correlations (Sohrabi *et al*., 2019) [1] that were previously inaccessible. This study leverages the power of K-Means clustering and Principal Component Analysis (PCA) to dissect a voluminous dataset brimming with diverse pharmacy performance metrics. These advanced analytical tools facilitate the segmentation of pharmacies into distinct groups based on performance characteristics (Kevrekidis *et al*., 2018) [7], providing a clearer picture of operational efficiencies and inefficiencies.

By harnessing these advanced analytical tools (Flynn, 2019) [5], the study aims to unearth hidden patterns, unveil latent correlations, and ultimately furnish healthcare stakeholders with actionable insights to optimize pharmacy operations and enhance patient outcomes (Policarpo *et al*., 2019) [6]. The use of K-Means clustering helps to group pharmacies with similar operational profiles, while PCA aids in the visualization and interpretation of these groups in a simplified two-dimensional space. This dual approach enhances the understanding of pharmacy performance (Konyak *et al*., 2018) [4] and provides a strategic framework for making data-driven decisions.

The implications of this study are significant for healthcare providers, policymakers, and pharmacy managers who seek to improve operational efficiency and patient care (Moya *et al*., 2019) [8]. By identifying the key factors that drive performance and understanding how different pharmacies operate, stakeholders can develop targeted strategies to address specific areas of weakness and build on areas of strength.

This study emphasizes the importance of implementing advanced machine-learning techniques in the healthcare sector to unlock new levels of insight and optimization in pharmacy management.

2. Materials and Methods

The dataset used in this study comprises 100,010 examples obtained from a realistic simulation of pharmacy operations. It includes the following features: Sales Revenue (INR), Prescription Volume, Medication Adherence Rate (%), Inventory Turnover, Labor Costs (INR), Customer Satisfaction Score, Pharmacy Size (Sq.ft), Average Transaction Value (INR), Profit Margin (%), Prescription Fill Rate (%), Generic Dispensing Rate (GDR) (%), Patient Wait Times (min), Medication Error Rate (%), Return on Investment (ROI) (%), Customer Retention Rate (%), Medication Therapy Management (MTM) Utilization (%), Adverse Drug Event (ADE) Reporting Rate (%), and others. The data was stored in a CSV file and imported into the analysis environment using Python. The efficiency of a pharmacy is significantly influenced by various metrics, including Sales Revenue, Prescription Volume, and Medication Adherence Rate. Higher sales revenue and prescription volume often indicate robust operations and demand, but these must be balanced with efficient inventory turnover to avoid overstock or stockouts. Labor Costs need to be optimized to ensure profitability without compromising service quality, which directly affects Customer Satisfaction Scores. Pharmacy Size and Average Transaction Value impact the operational scale and revenue per customer. A higher Profit Margin indicates financial health, while an optimal Prescription Fill Rate and Generic Dispensing Rate reflect service efficiency and cost-effectiveness. Reducing Patient Wait Times (min) and Medication Error Rates enhances customer experience and safety. Return on Investment measures overall financial efficiency, whereas Customer Retention Rate reflects loyalty and sustained business. Effective Medication Therapy Management (MTM) Utilization ensures better patient outcomes, and Adverse Drug Event (ADE) Reporting Rate is crucial for monitoring safety and improving care quality. These metrics provide a comprehensive view of a pharmacy's operational efficiency and effectiveness.

Pre-processing steps were undertaken to handle missing values, normalize numeric features, and encode categorical variables. Outliers were identified and managed to ensure the robustness of the clustering process. Numeric features were normalized using the StandardScaler to ensure that all features contributed equally to the analysis.

K-Means clustering was selected for its simplicity and effectiveness in segmenting data based on similarities. The optimal number of clusters was determined using the elbow method, which balances the trade-off between the number of clusters and the explained variance. The Within-Cluster Sum of Squares (WCSS) was calculated for different values of k (number of clusters), and the optimal k was identified by the point where the WCSS curve starts to flatten. Principal Component Analysis (PCA) was performed to visualize the clusters in a two-dimensional space, aiding in the visualization of the high-dimensional data. The cluster centres were analysed to understand the characteristics of each cluster. An inverse transformation was applied to the cluster centres to interpret the results in the original feature space.

3. Results and Discussion

The Elbow Method is a commonly used technique to determine the optimal number of clusters (k) in a dataset. The Fig 1 displays the Within-Cluster Sum of Squares (WCSS) against the number of clusters. The WCSS decreases as the number of clusters increases. This is expected as more clusters generally reduce the sum of distances of points within each cluster. The optimal number of clusters is typically identified at the "elbow point," where the rate of decrease sharply slows down. In this plot, the elbow appears to be at k=4, which is a reasonable choice for the number of clusters because adding more clusters beyond this point results in a marginal reduction in WCSS, indicating diminishing returns.

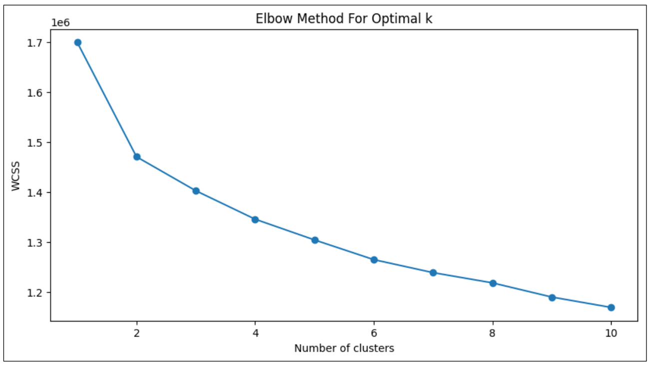

Fig 1: Elbow Method for Optimal k

The clustering analysis identified four distinct clusters of pharmacies based on their operational metrics. Fig 2 visualizes the clusters formed using Principal Component Analysis (PCA) for dimensionality reduction. The pharmacies are plotted on two principal components (PC1 and PC2), and each point represents a pharmacy, colored according to its cluster. The PCA visualization clearly depicted the separation between clusters, indicating well-defined groupings.

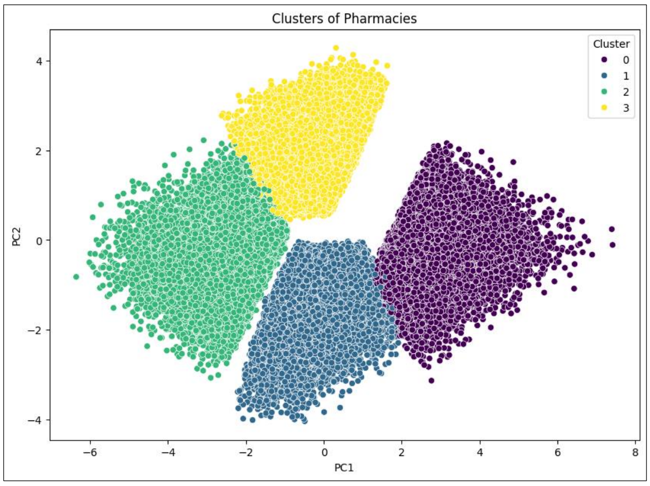

Fig 2: Clusters of Pharmacies

Notable fluctuations are observed between CP 03 to CP 05 and CP 07 to CP 08. ROI remains relatively stable but lower than profit margins, with CP 01 and CP 08 slightly exceeding 40% and CP 03 dipping below 20%. Pharmacies like CP 02, CP 04, and CP 07 maintain ROI within the 30-40% range. The data shows higher profit margins do not always correlate with higher ROI. Performance gaps suggest management efficiency, cost control, and revenue generation disparities.

Stable ROI in some pharmacies indicates consistent practices, while variable profit margins suggest market conditions or operational cost changes. The analysis highlights the need for targeted strategies to improve performance in lower-performing pharmacies and suggests adopting best practices from higher-performing ones to bridge performance gaps. // Cluster 0 represents pharmacies with high sales revenue, prescription volume, profit margin, and ROI. These pharmacies also have a larger average transaction value but lower customer satisfaction scores, prescription fill rates, and customer retention rates. Cluster 1 includes pharmacies with lower sales revenue, prescription volume, profit margin, and ROI. However, they have higher prescription fill rates and MTM utilization rates. Customer satisfaction scores and retention rates are average, and medication error rates are slightly higher. Cluster 2 represents pharmacies with the lowest sales revenue, prescription volume, profit margin, and ROI. These pharmacies have the highest labor costs, customer satisfaction scores, prescription fill rates, GDR, MTM utilization, and ADE reporting rates. Despite lower financial performance, they excel in customer satisfaction and service utilization. Cluster 3 includes pharmacies with high sales revenue, prescription volume, medication adherence rate, inventory turnover, and profit margin. They have lower prescription fill rates and average customer satisfaction scores. Despite having higher financial metrics, customer retention rates are lower, and MTM utilization is the lowest.

Clusters 0 and 3 exhibit higher sales revenue, prescription volume, and profit margins. These clusters are characterized by effective inventory turnover, higher medication adherence, and larger pharmacy sizes. Cluster 2 excels in customer satisfaction and service utilization metrics like MTM and ADE reporting despite lower financial performance. Higher prescription fill rates are observed in Clusters 1 and 2, whereas Clusters 0 and 3 have lower fill rates. Clusters 2 and 3 struggles with customer retention rates. Pharmacies in Clusters 0 and 3 likely have higher technology adoption and online services, contributing to their financial success. In contrast, Clusters 1 and 2 may benefit from improvements in these areas.

The analysis reveals that technology adoption, online services, and community engagement are pivotal in driving pharmacy performance. High-performing pharmacies excel in operational metrics and prioritize customer-centric services and community involvement. These findings suggest that pharmacies aiming to improve their performance should invest in technology, enhance online service offerings, and foster strong community ties. These interpretations help identify areas of improvement for different clusters, guiding strategic decisions to enhance pharmacy performance.

4. Conclusion

This study highlights the effectiveness of machine learning techniques, namely K-Means clustering and PCA, in analyzing and segmenting pharmacy performance data. By clustering pharmacies based on key performance metrics, we uncover distinct operational patterns that provide valuable insights into the strengths and areas for improvement across different pharmacy groups. The four identified clusters reveal diverse characteristics, from high sales revenue and prescription volume to varying customer satisfaction and medication adherence levels. These insights emphasize the critical role of technology adoption, online service enhancement, and community engagement in boosting pharmacy performance. The findings offer practical implications for pharmacy managers and healthcare stakeholders, guiding them towards data-driven decisions that can optimize operations and improve patient outcomes. Pharmacies with lower performance metrics can learn from high-performing clusters by adopting best practices, investing in technology, and focusing on customer-centric services. Future research can expand on this study by incorporating additional data sources and exploring more advanced machine learning algorithms to further refine the analysis. Overall, this study underscores the transformative potential of machine learning in healthcare analytics, paving the way for more efficient and effective pharmacy management strategies.

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