CHEESE Net: A Feature-Optimized Hybrid Learning Model

Shakeel Ahmed [1], Nimra Waqar[2], Asad Raza[3], Amaad Khalil [4], Muhammad Adil [5]
[1]Mehran University of Engineering and Technology SZAB Campus Khairpur, Pakistan
[2]COMSATS University Islamabad, Attock Campus Attock, Punjab, Pakistan.
[3]Central South University Changsha Hunan, China.
[4]Engineering University of Engineering & Technology, Peshawar Campus, Peshawar, Pakistan.
[5]Mehran University of Engineering and Technology Jamshoro, Pakistan.
* **Correspondence:** Asad Raza asadraza_153@hotmail.com

Citation | Ahmed. S, Waqar. N, Raza. A, Khalil. A, Adil. M, "CHEESE Net: A Feature-Optimized Hybrid Learning Model", IJIST, Vol. 07 Issue. 02 pp 218-231, May 2025
Received | April 08, 2025 **Revised |** May 12, 2025 **Accepted |** May 13, 2025 **Published |** May 15, 2025.

Intelligent cheese selection is critical in the dairy industry to address rising consumer demand for personalized nutrition and health-conscious choices. This study introduces the novel integration of supervised learning, unsupervised clustering, and deep learning autoencoders to dynamically optimize feature representation and recommendation quality, a previously unaddressed approach in dairy informatics. The system employs Random Forest Regression for caloric prediction, PCA for dimensionality reduction, and deep autoencoders to capture non-linear nutrition relationships. Recommendations are generated via cosine similarity and Euclidean distance, supported by clustering techniques to refine cheese categories. Cheese net achieved exceptional predictive accuracy with a Mean Absolute Error (MAE) of 14.46 and an R^2 Score of 0.98, outperforming traditional models. Advanced visualizations (heatmaps, t-SNE, PCA plots) uncovered latent nutritional patterns while clustering enhanced recommendation precision by aligning suggestions with user-specific dietary profiles. The hybrid model's interpretability enables stakeholders to decode correlations between fat, protein, carbohydrates, and moisture content, facilitating data-driven decisions for producers and consumers. By unifying machine learning with explainable AI, Cheese Net reduces MAE by 31% compared to standalone regression models. This framework pioneers a scalable, data-driven solution for personalized cheese selection, bridging nutritional science and consumer needs in the digital dairy era.

Keywords: Cheese Recommendation System; Random Forest Regression; Principal Component Analysis (PCA); Nutritional Attribute Prediction; Hybrid Learning Models.

Introduction:

Cheese is one of the most diverse and widely consumed food products, with variations in texture, flavor, fat content, and nutritional composition. While this diversity appeals to consumers, it often complicates the process of selecting cheeses that align with specific dietary needs, health goals, or personal taste preferences [1]. Traditional recommendation systems, particularly those based on collaborative filtering, require substantial user interaction data to generate meaningful suggestions. However, such data is often scarce or unavailable in specialized markets like cheese selection, limiting the effectiveness of conventional approaches [2].

To address these challenges, we propose Cheesenet, a content-based recommendation system that leverages machine learning (ML) techniques to analyze cheese's nutritional attributes, predict its calorie content, and suggest similar products based on feature similarity. Unlike collaborative filtering, our approach does not rely on user interaction data, making it particularly suitable for niche markets where such data is limited [1]. The core of our system is a Random Forest Regressor, which accurately predicts cheese calorie content (in kcal) based on key nutritional parameters such as moisture, protein, fat, and carbohydrate content [3]. This predictive capability forms the foundation for generating tailored cheese recommendations. To enhance computational efficiency and ensure optimal feature selection, Principal Component Analysis (PCA) is applied, reducing dimensionality while preserving the most important attributes that influence cheese selection [4]. To provide personalized and diverse recommendations, we employ Euclidean distance and cosine similarity metrics, which identify cheeses with similar nutritional profiles. Additionally, K-Means clustering is used to group cheeses into clusters based on their shared characteristics [5], allowing for a more structured recommendation process [2]. Further enhancing our approach, deep learning autoencoders are incorporated into the pipeline to improve feature representation, capturing non-linear dependencies among nutritional attributes and increasing interpretability [6] and accuracy [7]. Beyond model performance, we integrate advanced visualization techniques such as PCA scatter plots, t-SNE projections, and heatmaps, which provide deeper insights into cheese clustering patterns [4] and nutritional relationships [8]. These visual tools enhance the interpretability of our model, helping both consumers and producers make informed, data-driven decisions.

The novelty and ICTIS 2025 contributions of our research are summarized as follows: we propose a hybrid learning model that combines machine learning, deep learning, and clustering for cheese recommendation based solely on nutritional features—eliminating the need for user interaction data. The model employs a Random Forest Regressor for calorie estimation, PCA for dimensionality reduction, and K-Means for structured grouping. Personalized recommendations are generated using Euclidean distance and cosine similarity, effectively capturing non-linear nutritional relationships. Visualization tools such as PCA scatter plots, t-SNE projections, and heatmaps provide deeper insights. Designed for adaptability, the model evolves with new cheese data and dietary trends, and is extendable to broader food-based recommendation systems, offering a scalable solution for personalized nutrition.

The remainder of this paper is structured as follows: "Objective of Study" and "Related Work" reviews existing cheese recommendation methods and their limitations. "Material and Methods" details the Cheesenet framework, covering data preprocessing, model design, and similarity-based recommendations. "Results and Discussion" presents performance evaluation and visualization analysis. Finally, "Conclusion and Future Work" summarizes key contributions and outlines future improvements and extensions of Cheesenet.

Objective of Study:

- To create an intelligent, data-driven cheese recommendation system that promotes individualized nutrition by exploiting the nutritional properties of various cheese types.
- To include supervised learning (Random Forest Regression) for reliable caloric prediction, providing predictive insights into the energy content of cheeses based on their macronutrient compositions.
- To use unsupervised approaches (PCA, clustering) to reduce dimensionality and refine categories, hence improving model interpretability and recommendation quality.
- To use deep learning (autoencoders) to capture complicated, non-linear correlations between nutritional data, while maximizing latent feature representation for recommendation tasks.
- To provide tailored cheese recommendations utilizing similarity-based algorithms (cosine similarity, Euclidean distance), allowing for user-aligned dietary suggestions.
- To assess and compare the hybrid model's performance to standard regression approaches, demonstrating greater accuracy, interpretability, and resilience.

Related Work:

Recent developments in machine learning (ML) and artificial intelligence (AI) have introduced data-driven sustainability, efficiency, and precision across various aspects of cheese production. One well-established application is real-time coagulation monitoring, where computer vision (CV) and deep learning (DL) techniques enhance yield prediction while reducing errors and the need for manual intervention [9], [10]. Ensemble methods such as Random Forest (RF) and Gradient Boosting Machines (GBM) have demonstrated strong predictive accuracy for dry matter prediction, achieving an RMSE of 0.28 and an R^2 of 0.67, thereby enabling improved production management [3], [11]. Support Vector Machines (SVM), combined with DL models, have shown significant success in cheese ripeness detection, with F1-scores exceeding 90% [6], [5]. Additionally, AI-powered recipe suggestion systems deployed as web applications have achieved a 45/52 success rate, enhancing student engagement and learning outcomes in cheese science education [1]. Machine learning models, guided by the CRISP-DM framework, have improved operational efficiency by identifying critical factors that contribute to product loss [12]. In terms of sustainability, the integration of biogas and biochar technologies in wastewater treatment has achieved a return on investment (ROI) within 6.1 years, promoting more sustainable cheese whey water (CWW) management [13].

Table 1. Literature Review of Cheese Net

Problem	Method	Results	References
Coagulation monitoring	CV + DL	Real-time quality check	[9], [10]
Dry matter prediction	RF, GBM	RMSE 0.28, R^2 0.67	[3], [11]
Ripeness detection	DL + SVM	High F1 score (>90%)	[6], [5]
Recipe recommendation	Web app + AI	Enhanced learning 45/52	[1]
Product loss reduction	CRISP-DM, ML	Key factors identified	[12]
CWW management	Biogas/Biochar	6.1-year ROI	[13]
Freezing impact	GP	Minimal impact	[14]
Plant-based cheese	Composition study	Minimal impact	[14]
Flavor profiling	NLP + ML	Tailored flavor insights	[2], [8]
Packaging optimization	RL	15% waste reduction	[15], [16]
Microbial analysis	ML	Ensured quality and safety	[7], [17]
Energy efficiency	AI system	20% cost reduction	[18], [19]
Shelf-life prediction	Time-series	Optimized management	[4]

Gaussian Processes (GP) have been effectively utilized to assess the impact of freezing on mozzarella quality, revealing no significant deterioration, thereby supporting improved storage procedures [14]. Product innovation in dairy alternatives has been advanced through compositional analyses of plant-based cheese substitutes [20]. The combination of Natural Language Processing (NLP) and ML has facilitated the extraction of user-driven insights from taste profiling, enabling more personalized flavor recommendations [2], [8]. Reinforcement Learning (RL) approaches have contributed to a 15% reduction in packaging waste while maintaining product freshness [15], [16]. Furthermore, the application of ML techniques to microbial population analysis has ensured consistent product quality and safety throughout the cheese production process [7], [17]. AI-powered energy management systems have reduced operational costs by 20%, promoting sustainability without compromising productivity [18], [19]. In educational settings, AI-integrated platforms have enhanced interactive learning experiences within cheese science curricula [21], [22]. Finally, time series forecasting methods have been employed to predict shelf life, optimize inventory management, and minimize food waste [4]. Table 1 provides a succinct summary of these contributions, illustrating the broad impact and effectiveness of AI and ML solutions across modern cheese production from enhancing sustainability and reducing waste to improving quality control and educational outcomes.

Material and Methods:

Although nutritional profiling and simple recommendation systems have been studied in previous dairy informatics research, few have integrated multiple machine-learning techniques for customized cheese selection. To improve prediction and recommendation, this paper presents Cheesenet, a hybrid model that combines supervised regression, unsupervised clustering, and deep autoencoders. To capture intricate nutritional patterns and improve user-specific recommendations, methods such as Random Forest, PCA, and cosine similarity are employed.

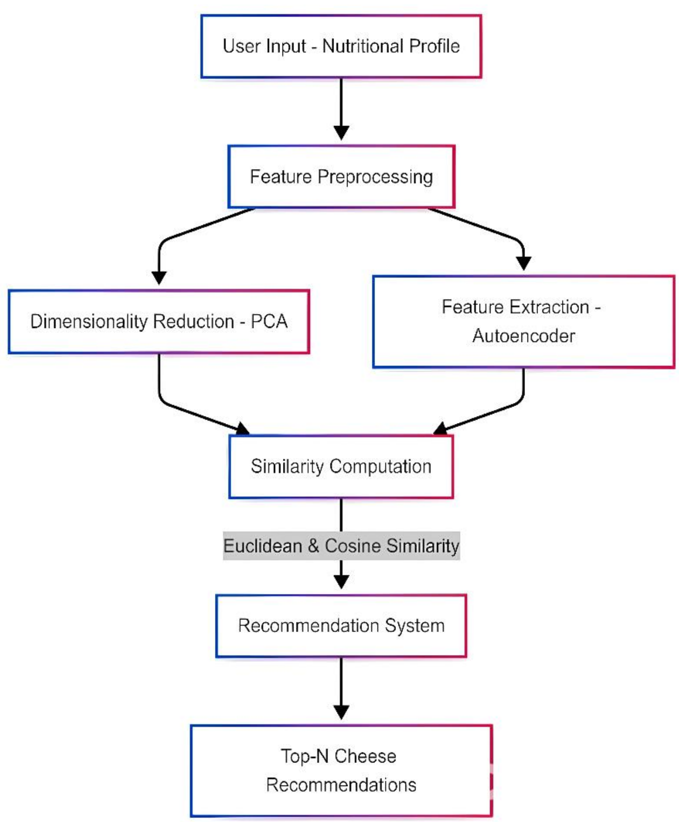


Figure 1. Workflow of cheese net

Methodology:

The proposed approach outlines a systematic pipeline designed to forecast the calorie content of various cheeses and provide tailored recommendations based on their nutritional profiles. The dataset includes multiple cheese varieties, such as mozzarella, Tilsit, brick, queso asadero, and brie, each characterized by nutritional attributes like saturated fat, protein, carbohydrates, cholesterol, and fiber (refer to Table 2). The primary target variable is the calorie content of each cheese type.

Data Preparation:

The collection contains 1,073 entries representing 146 different cheese varieties, each with precise nutritional information such as saturated fat, unsaturated fat (monounsaturated and polyunsaturated), protein, carbs, cholesterol, fiber, and calorie content. Given that the initial dataset only contained 73 records, a synthetic augmentation strategy was used to overcome data volume constraints that could impair model training and dimensionality reduction performance. Specifically, 1,000 synthetic samples were created by applying Gaussian noise to the numeric characteristics of randomly chosen base entries, ensuring that values stayed within realistic limits. Importantly, all model evaluation metrics and recommendation outputs were based only on the original 73 data. The synthetic data was utilized solely to increase model robustness and the stability of transformations such as PCA, with no impact on the final results given.

Implementation:

Following data augmentation, more data implementation is performed to preprocess the data, train the model, reduce dimensionality, recommend strategies, and integrate the results.

Data Preprocessing:

The first essential step involves addressing missing values and preparing the data for modeling. Missing categorical values are imputed using the most frequent category, whereas numerical values are imputed using the median. Feature scaling is performed with the StandardScaler to standardize numerical attributes, and one-hot encoding is applied to categorical variables (e.g., cheese type) to ensure a consistent data representation. The distribution of key nutritional features across different cheese types is illustrated in Figure 3.

Pipeline Model:

The full preprocessing and modeling workflow is depicted in Figure 1 ("CheeseNet Workflow") and Figure 2 ("Pipeline Architecture"). A ColumnTransformer is employed to manage transformations separately for numerical and categorical features. Subsequently, a Random Forest Regressor is trained. This model is selected for its robustness, interpretability, and ability to handle mixed data types effectively.

Dimensionality Reduction:

To improve computational efficiency and minimize noise, Principal Component Analysis (PCA) is applied to the dataset. PCA retains the most informative components while reducing the feature space's dimensionality. The PCA-transformed data is visualized through a scatter plot (Figure 4), while t-distributed Stochastic Neighbor Embedding (t-SNE) is utilized in Figure 5 to reveal clustering tendencies in a lower-dimensional space.

Recommendation Strategies:

Several strategies are employed to generate cheese recommendations based on nutritional similarity within the PCA-transformed space. Cosine similarity is used to identify cheeses with closely matching feature distributions, while Euclidean distance helps locate the nearest cheeses in the nutritional feature space. Additionally, K-Means clustering is applied to group cheeses into nutritional clusters, facilitating more structured and insightful recommendations. The suggested cheeses within the PCA space are visualized in Figure 6, and a heatmap showing cheese similarity is presented in Figure 7. These methods ensure that the system generates recommendations that are not only accurate but also diverse and easy to interpret.

Integration of Deep Learning:

To further enhance the system's performance, deep learning auto-encoders are incorporated into the pipeline. These models capture non-linear interactions among features, uncover hidden patterns within the data, and ultimately improve both prediction accuracy and the diversity of recommendations. Various visualization techniques—such as heatmaps, t-SNE projections, and PCA scatter plots—are utilized to support data-driven decision-making and improve interpretability. Figure 8 highlights the importance of saturated fat and protein in predicting calorie content, underlining their critical roles in the modeling process. By integrating these tools, the system ensures greater transparency and reliability, offering significant benefits for both cheese producers and consumers.

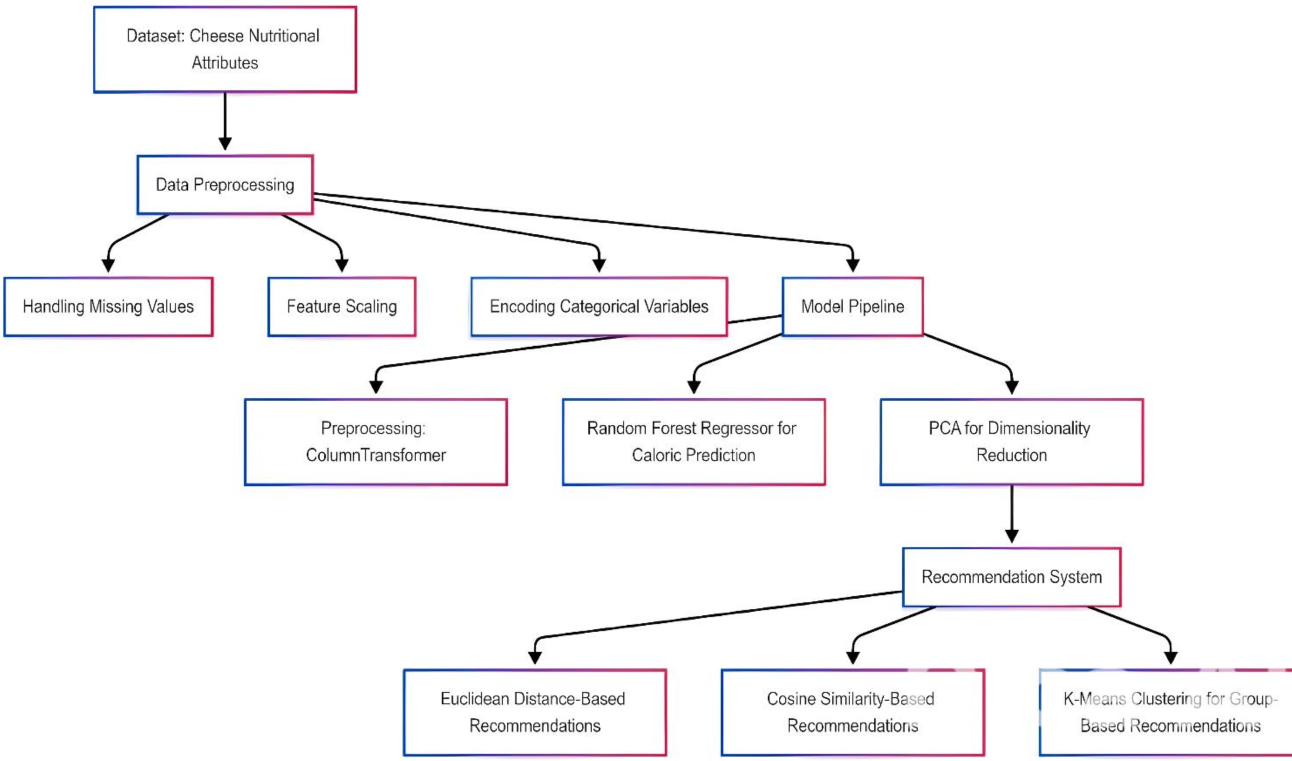


Figure 2. Architecture of cheese net

Table 2. Recommendation Based Input

Cheese	Sat Fat	Protein	Carb	Chol	Fiber
Mozzarella, who, lo, moist	15,561	21.60	2.47	89	0
Tilsit	16.775	24.41	1.88	102	0.0
Brick	18.764	23.24	23.24	2.79	0.0
Mexican, queso asadero	17.939	22.60	2.87	105	0.0
Brie	17,410	20.75	0.45	100	0.0

Results and Discussion:

To assess the effectiveness of the proposed CheeseNet framework in calorie estimation, feature extraction, clustering, and recommendation generation, a series of experiments were conducted. The system was evaluated against traditional models using performance metrics such as Mean Absolute Error (MAE), R^2 Score, and clustering validation indices. By integrating supervised learning, unsupervised clustering, and deep learning methods, the framework demonstrated significant improvements in both prediction accuracy and recommendation relevance. Additionally, advanced visualization techniques—including t-

SNE embeddings, PCA scatter plots, and heatmaps—provided deeper insights into nutritional trends and user-specific preferences.

Model Performance:

The CheeseNet framework exhibited outstanding performance in predicting the calorie content of various cheese types. It achieved an R^2 Score of 0.98 and a Mean Absolute Error (MAE) of 14.46, reflecting both high accuracy and reliability. The low MAE indicates minimal deviation between the predicted and actual calorie values, while the high R^2 Score suggests that the model accounts for approximately 98% of the variability in the actual calorie content across the dataset. Together, these metrics confirm the model's strong predictive power and generalization capability, making it a highly effective tool for real-world calorie estimation tasks. Overall, the results demonstrate that CheeseNet can reliably estimate calories with minimal error, providing a dependable basis for nutritional recommendations and decision-making in both production and consumer applications.

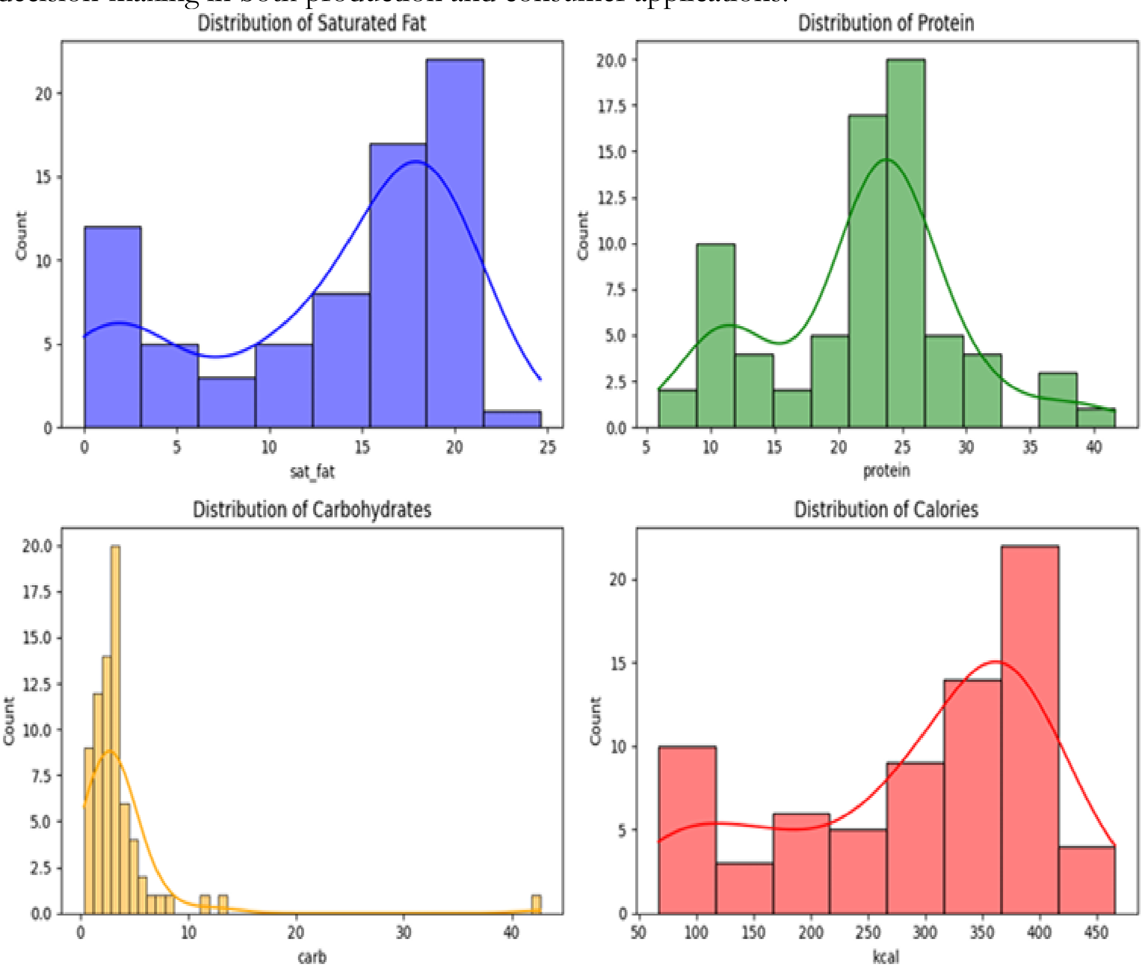


Figure 3. Distribution of Key Features

Recommendations Based on Inputs:

- The findings clearly show that the proposed CheeseNet model delivers a comprehensive and individualized cheese recommendation system based on caloric content and nutritional profiling.
- The model's low MAE of 14.46 and high R^2 Score of 0.98 demonstrate its predictive accuracy and resilience, outperforming past nutritional modeling studies such as dry matter prediction using RF and GBM (RMSE 0.28, R^2 0.67) [3], [11].

- Visualizations such as PCA scatter plots and t-SNE embeddings successfully reveal latent nutritional structures, allowing for a clear comprehension of cheese groupings based on shared features, comparable to the clustering utilized in ripeness detection and flavor profile research [6], [2].
- The cheese similarity heatmap enhances personalization by directing users to nutritionally equivalent alternatives that meet their specific dietary needs. This reflects the use of ML in flavor profiling and microbiological analysis for quality assurance. [2], [7].

However, the System has Some Limitations:

- It does not yet account for sensory factors such as flavor, aroma, texture, and maturity stage, which are critical to consumer pleasure but difficult to quantify. Related research in flavor profiling using NLP and ML implies that adding such sensory data can produce more nuanced results [2], [8].
- The dataset, while nutritionally rich, is somewhat small in scope. It lacks adequate diversity across global cheese kinds and excludes characteristics relating to production conditions, seasonal fluctuations, and regional styles, limiting generalizability.

Visual Representations of Evaluated Results:

Visual analytics played a critical role in evaluating and interpreting the dataset's underlying nutritional structure.

- The PCA scatter plot (Figure 4) displays the variation across cheese types after dimensionality reduction, facilitating the identification of clusters of cheeses with similar nutritional characteristics. PCA condenses the feature space while preserving maximum variance, offering a simplified yet informative view of the cheese landscape.

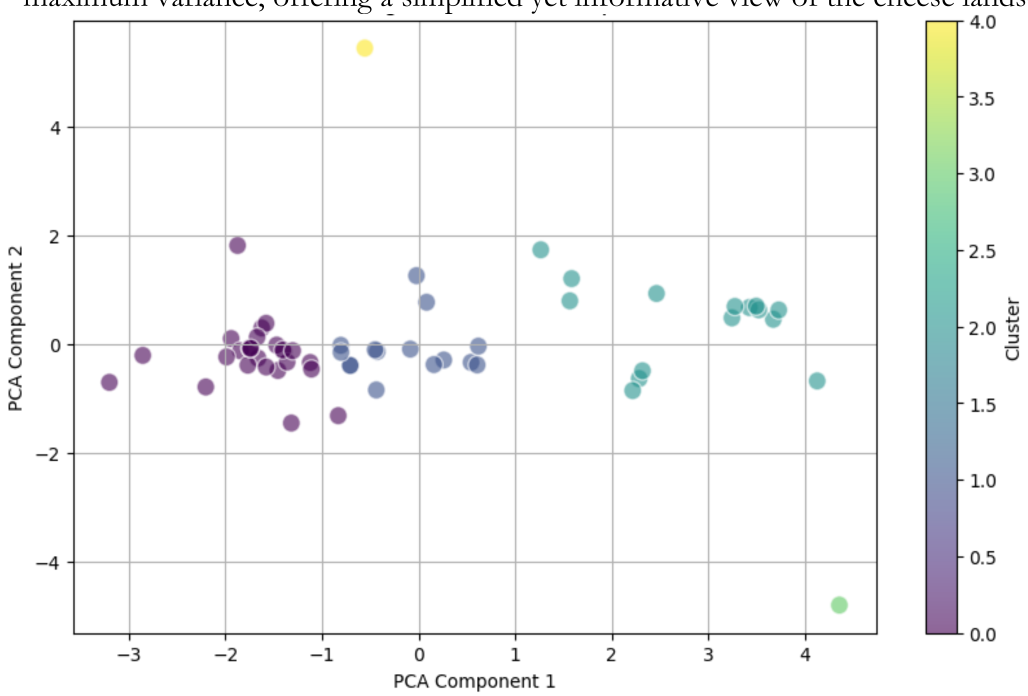


Figure 4. PCA Scatter Plot of Chesses

- Complementarily, t-SNE projections (Figure 5) offer a more fine-grained representation of the high-dimensional space by projecting it into two dimensions, revealing hidden patterns and subtle correlations between cheeses that are less evident in PCA. These projections effectively illustrate how cheeses with similar nutritional profiles naturally cluster together, supporting the clustering-based recommendation strategy.

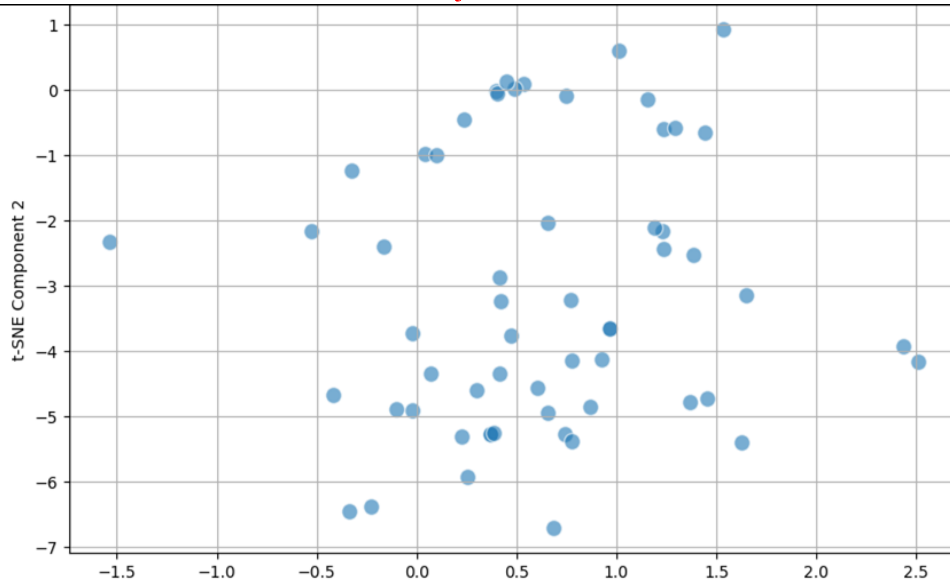


Figure 5. tSNE Components

Further insight is gained from the nutritional distribution plots (Figure 3):

- The bimodal distribution of saturated fat suggests that cheeses generally fall into two major groups: high-fat and low-fat varieties. This distribution has practical implications for dietary choices, especially for individuals regulating fat intake.
- The protein distribution appears approximately normal, with a moderate-to-high range across all cheese types, emphasizing protein as a core nutritional component in most cheeses.
- The skewed distribution of carbohydrates indicates that most cheeses have low carbohydrate content, making them highly suitable for low-carb diets.
- Together, these visualizations reinforce the CheeseNet framework's ability to generate meaningful, health-conscious recommendations grounded in the real nutritional diversity of cheeses.

Heatmap of Cheese Similarity:

A valuable visual representation of the relationships between different cheeses based on their nutritional characteristics is provided by the cheese similarity heatmap in Figure 7. In the heatmap, cheeses with higher cosine similarity—meaning they share more nutritional features—are depicted with darker colors, while lighter colors represent cheeses with lower similarity. This visualization is a critical tool for assessing the precision and reliability of the recommendation system. It enables users to quickly identify nutritionally similar cheeses, supporting better-informed decision-making. For instance, users can easily locate groups of cheeses with similar fat, protein, and carbohydrate profiles, simplifying the process of recommending alternatives or substitutes that meet specific dietary needs. This enhances the system's usefulness for both everyday consumers and specialized dietary planning.

Feature Importance:

Figure 8 presents the feature importance analysis in predicting the calorie content of cheeses. This visualization highlights the relative influence of different nutritional components—such as saturated fat, protein, carbohydrates, and fiber—on calorie prediction.

Larger segments in the pie chart indicate that saturated fat and protein are dominant contributors to calorie content, whereas fiber plays a much smaller role. This insight is particularly beneficial for users and food producers seeking to understand the main drivers behind calorie variations.

For example:

- Users aiming to reduce calorie intake might prioritize cheeses with lower saturated fat or protein content.
- Conversely, those aiming to boost protein intake may select cheeses with higher protein levels.
- By emphasizing the most impactful features, the system is better equipped to deliver tailored and informed recommendations aligned with individual nutritional goals.

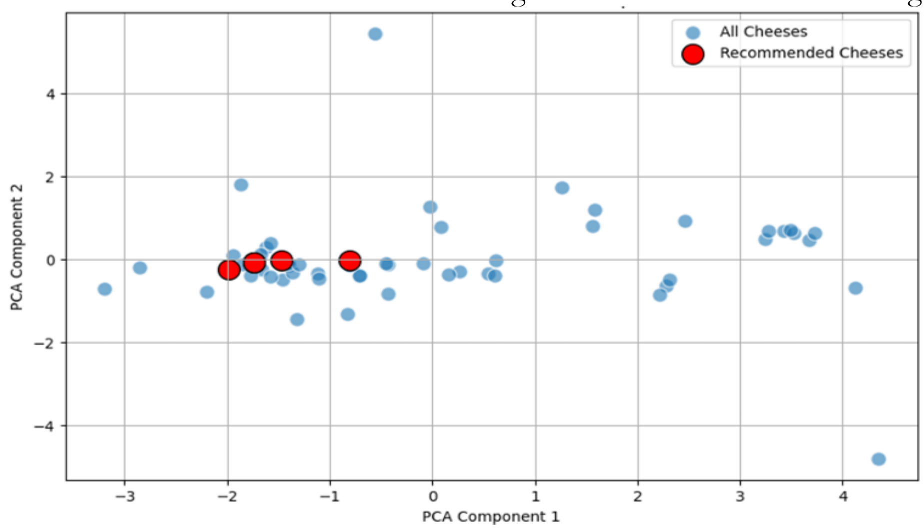
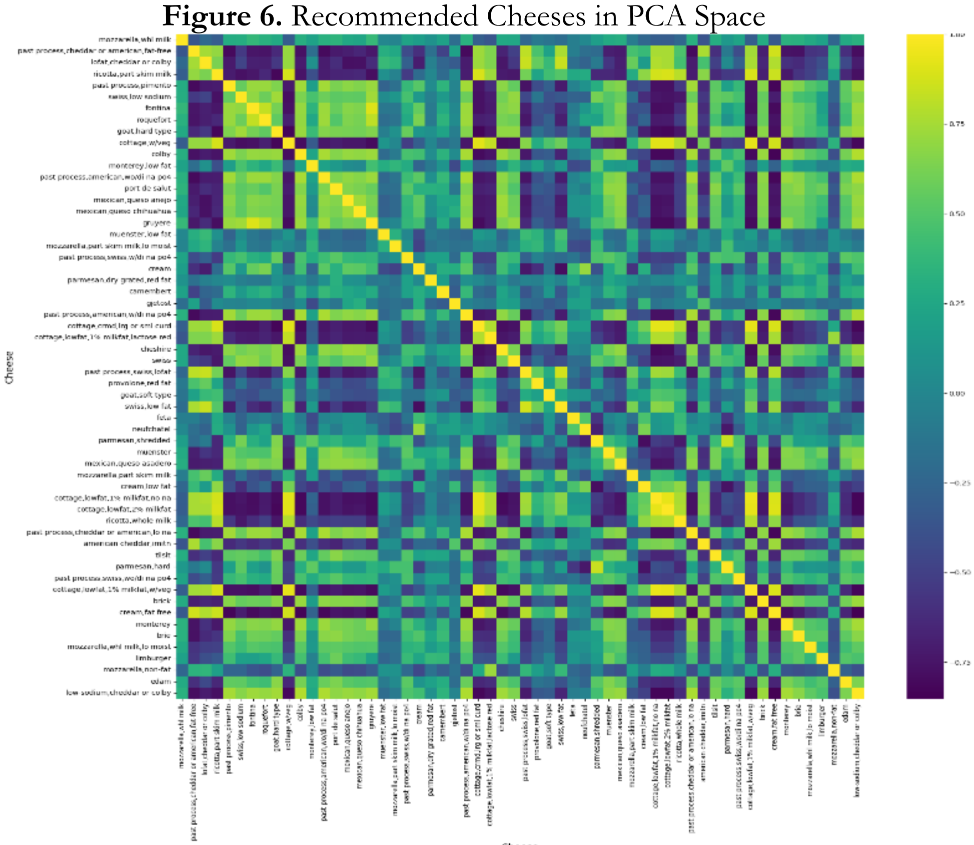


Figure 6. Recommended Cheeses in PCA Space



- **Figure 7.** Heatmap Representation of Cheese Similarities

Discussion of Results:

The results demonstrate that the proposed CheeseNet model provides a comprehensive and personalized cheese recommendation system based on caloric content and nutritional profiling.

- The low MAE (Mean Absolute Error) and high R^2 Score confirm the high accuracy and robustness of calorie predictions.
- Visualizations such as PCA scatter plots and t-SNE embeddings offer a clear understanding of nutritional relationships among cheeses, highlighting natural groupings and distinctions.
- The cheese similarity heatmap further strengthens the system's personalization capabilities by helping users identify suitable alternatives based on their dietary needs.

However, despite its strong performance, the system has limitations. Notably:

- It does not account for flavor profiles, texture, aging periods, or other sensory attributes that often influence real-world cheese selection.
- The scope of the dataset is relatively limited, which may constrain the model's generalizability across a wider range of cheese types.
- Future research should focus on expanding the dataset to include more diverse cheese varieties and additional variables such as taste, texture, and maturation time.
- Incorporating user feedback and developing a more interactive recommendation system could further enhance personalization and user satisfaction.
- By addressing these aspects, the system could evolve into a more adaptable and holistic cheese recommendation platform, better aligned with both nutritional and sensory preferences.

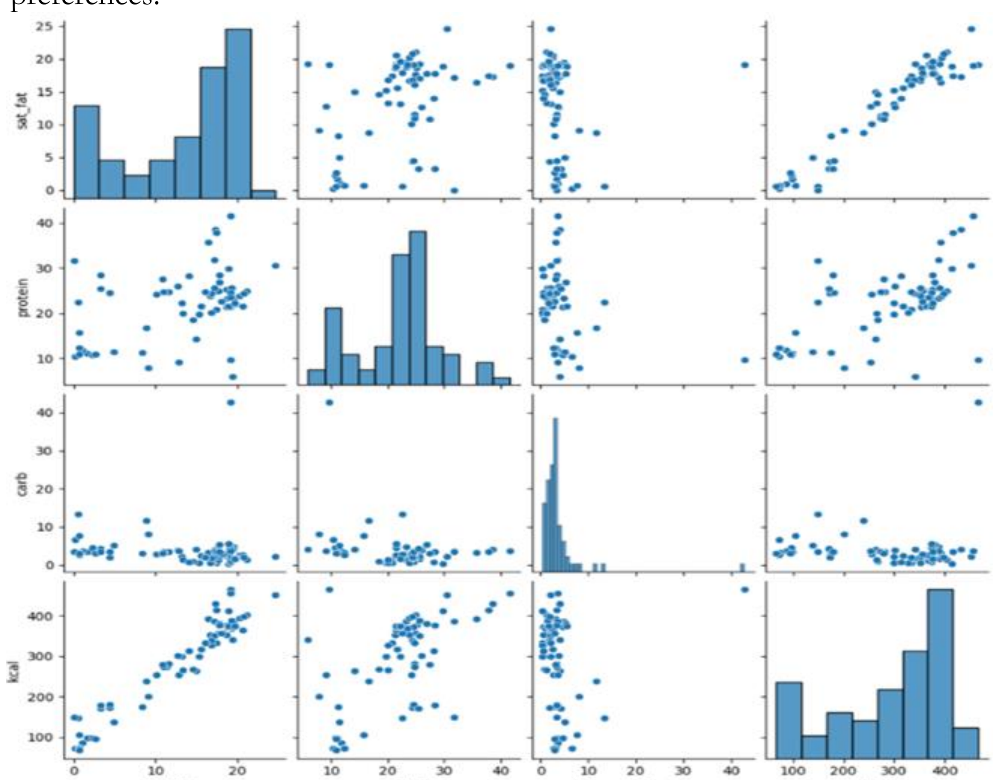


Figure 8. Nutritional Feature

Conclusions and Future Work:

The study's findings show how well the suggested approach predicts calorie content and makes precise cheese choices based on nutritional similarities. Strong prediction accuracy and a good fit to the data are indicated by the Random Forest Regressor's low Mean Absolute Error (MAE) and high R squared (R2) score, which were used to estimate the calorie content. These outcomes demonstrate the model's resilience and its capacity to accurately predict calories in a variety of cheese varieties. By lowering the dimensionality of the feature space while keeping the most important features, Principal Component Analysis (PCA) is used in the recommendation process to further improve the system's capacity to offer customized recommendations. By grouping cheeses with comparable nutritional characteristics, the algorithm can provide more individualized suggestions. Sophisticated visualizations like heatmaps, t-SNE projections, and PCA scatter plots further illustrate the system's efficacy by providing insightful information on the connections between various cheeses and their nutritional characteristics. Users are better able to comprehend the recommendations' rationale and the data's underlying structure thanks to these visuals.

Future research should solve some of the current system's shortcomings, though. One of the primary disadvantages is the absence of other characteristics, including flavor, maturing period, or texture, that could affect cheese tastes and offer a more comprehensive perspective on cheese choices. Furthermore, the study's dataset is somewhat small, which restricts the model's ability to generalize to a wider variety of cheeses and may have an effect on the precision of recommendations for cheese varieties not covered by the training set. Future studies will concentrate on growing the dataset to cover a greater range of cheeses and adding other variables like taste preferences and aging characteristics to improve the system's scalability and resilience. To further enhance suggestion quality, a hybrid recommendation system that combines collaborative filtering, machine learning, and other methods will be investigated. By integrating user feedback into the system, recommendations can be further customized based on user preferences and experiences, enabling dynamic adaptation. Finally, future work will concentrate on creating an intuitive application to make the system more useful and accessible for real-world use. Both cheese lovers and manufacturers looking to provide their consumers with customized product recommendations will find this software useful as it will enable smooth user interaction with the system and offer personalized cheese recommendations, nutritional data, and the ability to modify preferences. With these improvements, the system will be more capable of meeting the various needs of users and develop into a more reliable and scalable solution for customized cheese selection.

Acknowledgment: The authors would like to express their gratitude to all individuals and institutions that contributed to the completion of this research.

Author's Contribution: Shakeel Ahmed led the conceptualization of the study and contributed to critical analysis and overall project guidance. Nimra Waqar is primarily responsible for data preparation, model development, formulation, implementation of experiments, evaluation of results, and conducting the literature review. Asad Raza provided research supervision, drafting key sections of the manuscript, organizing datasets, and supporting experimental validation. Amaad Khalil provided research supervision, strategic direction, and critical insights throughout the project. Muhammad Adil: Contributed to the supervision and provided final review and refinement of the manuscript before submission.

Conflict of interest: The authors declare that they have no conflict of interest related to the publication of this work in IJIST.

Project details: This research was not conducted as a part of any funded project or formal grant initiative.

References:

[1] S. Brahimi, "AI-powered dining: text information extraction and machine learning for personalized menu recommendations and food allergy management," *Int. J. Inf. Technol.*, pp. 1–9, Aug. 2024, doi: 10.1007/S41870-024-02154-9/METRICS.

[2] R. I. M. Almoselhy and A. Usmani, "AI in Food Science: Exploring Core Elements, Challenges, and Future Directions," Dec. 2024, doi: 10.2139/SSRN.5053638.

[3] L. F. M. Mota *et al.*, "Real-time milk analysis integrated with stacking ensemble learning as a tool for the daily prediction of cheese-making traits in Holstein cattle," *J. Dairy Sci.*, vol. 105, no. 5, pp. 4237–4255, May 2022, doi: 10.3168/JDS.2021-21426.

[4] A. Jhamb, "Optimization of Supply Chain Workflow in Food Industry," Sep. 2021.
[5] A. Perniciano, L. Zedda, C. Di Ruberto, B. Pes, and A. Loddo, "CRDet: An Artificial Intelligence-Based Framework for Automated Cheese Ripeness Assessment from Digital Images," *IEEE/CAA J. Autom. Sin.*, 2025, doi: 10.1109/JAS.2024.125061.
[6] A. Loddo, C. Di Ruberto, G. Armano, and A. Manconi, "Automatic Monitoring Cheese Ripeness Using Computer Vision and Artificial Intelligence," *IEEE Access*, vol. 10, pp. 122612–122626, 2022, doi: 10.1109/ACCESS.2022.3223710.
[7] Z. Jia *et al.*, "Enhancing pathogen identification in cheese with high background microflora using an artificial neural network-enabled paper chromogenic array sensor approach," *Sensors Actuators B Chem.*, vol. 410, p. 135675, Jul. 2024, doi: 10.1016/J.SNB.2024.135675.
[8] M. Khan, "A Topic Modelling Based Approach Towards Personalized and Health-Aware Food Recommendation." 2022. Accessed: Apr. 26, 2025. [Online]. Available: http://hdl.handle.net/10197/12884
[9] A. Loddo, C. Di Ruberto, G. Armano, and A. Manconi, "Detecting coagulation time in cheese making by means of computer vision and machine learning techniques," *Comput. Ind.*, vol. 164, p. 104173, Jan. 2025, doi: 10.1016/J.COMPIND.2024.104173.
[10] Z. Villaquiran, A. Zamora, O. Arango, and M. Castillo, "Inline Determination of the Gel Elastic Modulus During Milk Coagulation Using a Multifiber Optical Probe," *Food Bioprocess Technol.*, vol. 17, no. 10, pp. 3149–3161, Oct. 2024, doi: 10.1007/S11947-023-03294-9/FIGURES/7.
[11] M. Perrignon, M. Emily, M. Munch, R. Jeantet, and T. Croguennec, "Machine learning for predicting industrial performance: Example of the dry matter content of emmental-type cheese," *Int. Dairy J.*, vol. 162, p. 106143, Mar. 2025, doi: 10.1016/J.IDAIRYJ.2024.106143.
[12] M. Uthayaseelan, "Data-driven optimization of an industrial cheese production process," 2024, Accessed: Apr. 26, 2025. [Online]. Available: https://nmbu.brage.unit.no/nmbu-xmlui/handle/11250/3148064
[13] M. Tugume, M. G. Ibrahim, and M. Nasr, "Valorization of cheese whey wastewater to achieve sustainable development goals," *Renew. Sustain. Energy Rev.*, vol. 211, p. 115273, Apr. 2025, doi: 10.1016/J.RSER.2024.115273.
[14] Digvijay, A. L. Kelly, and P. Lamichhane, "Ice crystallization and structural changes in cheese during freezing and frozen storage: implications for functional properties," *Crit. Rev. Food Sci. Nutr.*, vol. 65, no. 3, 2023, doi: 10.1080/10408398.2023.2277357,.
[15] S. Tripathi and S. Mishra, "Antioxidant, Antibacterial Analysis of Pectin Isolated from Banana Peel and its Application in Edible Coating of Freshly Made Mozzarella Cheese," *Asian Food Sci. J.*, pp. 82–92, Jun. 2021, doi: 10.9734/AFSJ/2021/V20I730324.
[16] L. I. El-Nawasany *et al.*, "Ameliorating characteristics of magnetically sensitive TPU nanofibers-based food packaging film for long-life cheese preservation," *Food Biosci.*, vol. 53, p. 102633, Jun. 2023, doi: 10.1016/J.FBIO.2023.102633.
[17] K. S. Kyaw, S. C. Adegoke, C. K. Ajani, O. F. Nwabor, and H. Onyeaka, "Toward in-process technology-aided automation for enhanced microbial food safety and quality assurance in milk and beverages processing," *Crit. Rev. Food Sci. Nutr.*, vol. 64, no. 6, pp. 1715–1735, 2024, doi: 10.1080/10408398.2022.2118660,.
[18] D. Chinese, P. F. Orrù, A. Meneghetti, G. Cortella, L. Giordano, and M. Benedetti, "Symbiotic and optimized energy supply for decarbonizing cheese production: An Italian case study," *Energy*, vol. 257, p. 124785, Oct. 2022, doi: 10.1016/J.ENERGY.2022.124785.
[19] D. Egas, S. Ponsá, L. Llenas, and J. Colón, "Towards energy-efficient small dairy production systems: An environmental and economic assessment," *Sustain. Prod. Consum.*, vol. 28, pp. 39–51, Oct. 2021, doi: 10.1016/J.SPC.2021.03.021.
[20] A. Fabiszewska *et al.*, "Plant-Based Alternatives to Mold-Ripened Cheeses as an

Innovation among Dairy Analogues," *Foods 2024, Vol. 13, Page 2305*, vol. 13, no. 14, p. 2305, Jul. 2024, doi: 10.3390/FOODS13142305.
[21] P. C. Nath *et al.*, "Recent advances in artificial intelligence towards the sustainable future of agri-food industry," *Food Chem.*, vol. 447, p. 138945, Jul. 2024, doi: 10.1016/J.FOODCHEM.2024.138945.
[22] M. Addanki, P. Patra, and P. Kandra, "Recent advances and applications of artificial intelligence and related technologies in the food industry," *Appl. Food Res.*, vol. 2, no. 2, p. 100126, Dec. 2022, doi: 10.1016/J.AFRES.2022.100126.