Mobile Edge Networks with Machine Learning for Cosmetics Brand Positioning and Value Assessment

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Abstract:

To ensure that products gain wider consumer recognition and to build brand value, the cosmetics industry should focus on researching and developing better products while shaping a more favorable brand positioning to enhance its competitiveness. As intelligent mobile edge computing (MEC) continues to be integrated with Internet of Things (IoT) technologies, concerns arise over its capacity to handle the computational complexity of Machine Learning (ML) methodologies, particularly for large-scale IoT data monitoring. Despite these challenges, MEC provides many benefits, including real-time data processing and enhanced customer engagement. This paper aims to provide an Intelligent Dynamic Cosmetics Brand Positioning using Internet of Things-based Mobile Edge Computing (IDBP-IoT-MEC). One of the core methodologies used in this model is Support Vector Machines (SVMs), a powerful ML technique for classification and regression tasks. SVMs, known for their ability to handle high-dimensional data, will be utilized to assess and classify consumer preferences, brand perception, and market trends based on large-scale IoT data collected from edge devices. By applying SVMs, the IDBP-IoT-MEC framework can efficiently monitor and predict customer behavior, enabling more dynamic and accurate brand positioning in a highly competitive market. Moreover, validated assessment methodologies play a critical role in evaluating the efficacy of cosmetic products, promoting both innovation and competition. SVM-based evaluation models are a suitable and efficient tool for assessing the benefits of new cosmetics, providing insights into consumer needs and market trends. These insights can help cosmetic companies properly communicate product benefits to consumers while encouraging research and development of improved cosmetic formulations.

Keywords: Support Vector Machines (SVMs), Internet of Things (IoT), Edge Computing (EC), Cosmetics, Data analytics, Dynamic Brand Positioning.

1. Introduction:

Dermatology studies, diagnoses, and treats skin, nail, and hair problems. Dermatological diseases vary in aetiology, severity, and appearance. Humans have had skin disorders, but a more complete strategy to examining them didn't exist until the 18th and 19th centuries. Along with scientific advances, dermatology advanced. Since the nineteenth century's scientific revolution, dermatology has expanded rapidly.

Support Vector Machines (SVM) have become more popular in healthcare for screening, diagnosis, therapy, and epidemiological study. SVMs, one of the most powerful machine learning methods, excel in regression and classification. Hyperplanes may help support vector machines (SVMs) classify data and diagnose skin conditions based on clinical criteria. The development of SVM techniques is a result of advancements in computing hardware technology. Changes in consumer brand choice and consumption habits are evident outcomes of the competitive brand environment experiencing a major upheaval in the marketplace. One factor contributing to these shifts is the global expansion and evolution of private label brands (PLBs).

Therefore, the development and expansion of PLBs pose serious competitive threats to manufacturer brand managers and shed light on the brands' potential for the future. Marketers previously thought that customer brand consumption habits were relatively polarized and depended on socio-demographics to understand and segment the market. There are two types of consumers: those who are price-driven and willing to pay a premium for well-known and respected brands, and those who are more concerned with getting the most value by purchasing less expensive brands. Consequently, many companies have created brands and retail formats targeting the upper and lower echelons of the market, using a two-tier strategy.

Motivation: The expansion of the beauty and personal care industry necessitates the effective use of technological advances such as IoT and mobile edge computing. Competitive response becomes necessary as consumer demand for effective, efficient, and personalized products heightens. This project aims to offer a unique strategy—Intelligent Dynamic Brand Positioning (IDBP) using IoT and Mobile Edge Computing (MEC)—that will allow cosmetics companies to enhance their market positioning through real-time data analytics.

Problem Statement: Within shifting parameters dictated by market demand, one of the most challenging areas to retain a competitive brand position is the cosmetics industry. It is widely accepted that along with increased globalization, customer preferences have become more dynamic. Neither conventional marketing nor product strategy continues to suffice, nor can it be innovated upon easily. Moreover, it remains a challenge to measure and communicate the efficacy of cosmetic agent use. While industry leaders see the promise of mobile edge computing integrated with SVM techniques and IoT, they are concerned about the computational and scalability aspects of these technologies. This paper addresses the challenges of the research related to an IDBP framework that borders on the Internet of Things as well as mobile edge computing.

Main Contributions of this Paper:

- This paper presents intelligent brand positioning strategies utilizing MEC in the context of a makeup brand. The IDBP model incorporates MEC of IoT, allowing cosmetic industries to continuously reposition their brands in line with changing consumer behavior patterns derived from real-time information processing in a highly competitive, cyber-integrated market.
- The paper demonstrates the ability to measure the behavioral characteristics of consumers in real-time using SVM techniques within mobile edge networks. This facilitates the assessment of brand value and offers solutions for enhanced engagement with customers in the cosmetic domain.
- The paper presents a dynamic methodology for evaluating the effectiveness of cosmetic products. This method fosters development and competition by confirming that cosmetics are useful to buyers, helping businesses implement firm-customer approaches through agile brand positioning and value visioning.

Theremaining of this paper is structured as follows: In section 2, the related work of Brand Positioning and Value Assessment in Cosmetics is studied. In section 3, the proposed methodology of IDBP-IoT-MEC is explained. In section 4, the efficiency of IDBP-IoT-MEC is discussed and analysed. Finally, in section 5 the paper is concluded with the future work.

2. Review of literature

The marketplace is marked by both polarised and hybrid brand consumption patterns, making it difficult for the more conventional methodologies that depend on customer socio-demographics to define behaviour properly. To put solid plans into action, businesses must first be able to detect patterns of consumption or purchasing behaviour that explain the reasons behind brand choice. Marketers have found consumer psychographics to be an excellent foundation for segmenting consumers and predicting their purchasing behaviour.

Artificial Intelligence:

Consumer Behaviour Analysis using AI (CBA-AI):

Ameen, N. et al., [18] AI is changing the way companies engage with consumers. Customer experiences that are aided by AI have not been well studied empirically. As a result, the purpose of this research is to examine how AI-enabled shopping experiences might be enhanced via API integration. Based on the service quality model and the trust-commitment theory, provide a theoretical framework. Users of an AI service provided by a cosmetics company were polled via an online survey.

Marketing Decision Making Using AI (MDM-AI):

To survey existing works on the topic of AI's strategic uses and to identify areas in need of further investigation on the integration of AI into long-term marketing plans. The use of AI in determining long-term marketing decisions has received less attention. In many domains of management, the boundary of applying AI to decision-making is shifting from operational to strategic by Stone, M. et al., [19]. Strategic marketing choices using AI need immediate attention due to the competitive nature of the industry and lessons learnt from AI applications in military and related fields.

Building Brand Identity Using AI (BBI-AI):

Using a case study methodology, Ghodeswar, B. M. et al., [20] reviews the relevant literature. Brand positioning, brand message communication, brand performance delivery, and brand equity leveraging are the four pillars around which the paper rests as a framework for developing brand identity. Every department, intermediary, and supplier inside the firm contributes to the customer's experience with the brand, thus it's crucial that brand-building efforts be in sync with organisational procedures that fulfil consumer commitments.

Machine Learning:

Machine learning Based Bigdata Analysis (ML-BDA):

An new source that marketers may utilise to mine meaning at a high temporal frequency is online chatter, sometimes known as user-generated content. To deduce its significance, this paper proposes that it is necessary to identify the valence, labels, validity, importance, heterogeneity, and essential latent characteristics of quality satisfaction among consumers. Using unsupervised latent Dirichlet allocation, the authors provide a unified approach for this task by Tirunillai, S. et al., [21]. The user-generated content sample includes detailed information on product evaluations from fifteen different companies in five different marketplaces over four years.

Supply Chain Framework in Machine Learning (SCF-ML):

More and more, fashion e-commerce platforms are combining SC with recommender systems (RSs) to provide tailored product suggestions to customers. However, there is a dearth of research into improving SC for purposes related to the decision-making chain, such as online shopping. To help shape future studies, this paper compiles and synthesises existing material on fashion SC and how they relate to FRSC decision-making. As a field, fashion research is both timely and important since the industry is still in its early stages by Pereira, A. M. et al., [22].

Machine Learning in Decision Support System (ML-DSS):

ML in determining long-term marketing decisions has received less attention. In many domains of management, the boundary of applying ML to decision-making is shifting from operational to strategic, which is why this study is necessary. Strategic marketing choices using ML need immediate attention due to the competitive nature of the industry and lessons learnt from ML applications in military and related fields by Barrera, F. et al., [23]. The authors do not have access to the data necessary to confirm that ML is being used to make strategic marketing decisions since the information is considered confidential.

Internet of Things:

Advanced Brand Management in Edge Computing (ABM-EC):

Businesses have both possibilities and problems as a result of the explosion of user behaviour data caused by the proliferation of mobile devices and internet use. This study delves into user behaviour analysis within the big data framework, shedding light on its critical function in propelling innovation and informing strategic decision-making. To get things off, go over the value of user behaviour data and the recent tech developments like data mining, machine learning, and natural language processing that make it possible to gain profound understanding of user behaviour by Temporal, P. et al., [24].

Digital Marketing Transformation in IoT (DMT-IoT):

This research aims to understand how dynamic capabilities, as enabling mechanisms, may promote digital transformation by analysing the effects of digital transformation on customer value generation within the context of DMT working in the Made in Italy sectors. DMT from the culinary, fashion, and furniture design sectors were the subjects of our multi-case study research on digital transformation. Digital instruments help innovate the business models of the chosen DMT , opening up new distribution channels and methods to produce and provide value to client groups, according to the findings by Matarazzo, M. et al., [25].

Table 1: Summary of the related works

S. No	Methods	Advantages	Limitations
1	Consumer Behaviour Analysis using AI (CBA-AI)	Improves consumer experience, personalization, and efficiency in interactions	Empirical evidence is limited, not well-studied in diverse industries
2	Marketing Decision Making using AI (MDM-AI)	Enhances long-term strategic planning, competitive advantage	Lack of research on AI's strategic use, mainly focused on operational uses
3	Building Brand Identity using AI (BBI-AI)	Synchronizes brand-building efforts across departments, enhancing brand identity	Requires organizational alignment, difficult to maintain consistency across all touchpoints
4	Machine Learning Based Big Data Analysis (ML-BDA)	Allows extraction of consumer sentiment from large-scale data, improves marketing decisions	Complexity in identifying latent characteristics, heterogeneity of user-generated content
5	Supply Chain Framework in Machine Learning (SCF-ML)	Provides personalized product suggestions, improves customer satisfaction and supply chain efficiency	Limited research on SC's role in decision-making for online shopping
6	Machine Learning in Decision Support Systems (ML-DSS)	Enhances decision-making with data-driven insights, improves competitive edge	Access to strategic data is restricted, limiting comprehensive study
7	Advanced Brand Management in Edge Computing (ABM-EC)	Drives innovation and informed decision-making based on real-time user behavior data	Complexity in analyzing large-scale data and integrating insights into actionable strategies

8	Digital Marketing Transformation in IoT (DMT-IoT)	Promotes innovation, opens new distribution channels, and enhances customer value creation	Sector-specific research; findings may not be applicable across all industries

By integrating APIs, investigate how AI might enhance consumers' purchasing experiences. More study into the use of AI in marketing's long-term strategy choices is needed. Highlight the importance of organisational alignment with brand identity in their emphasis on AI in brand-building. ML assesses customer sentiment in online marketplaces, while in another, connections between fashion e-commerce supply chains and recommendation systems. Strategic marketing should make use of machine learning. Research on the internet of things has focused on the value that digital marketing may provide to businesses.

3. Proposed Method:

The medical and cosmetic dermatology include the former's emphasis on treating skin issues unrelated to disease, such as melasma, acne, freckles, age spots, and wrinkles. Although these dermatological problems are not life-threatening and do not directly affect a patient's physical health, they may have psychological consequences for people, such as low self-esteem and confidence, and long-term negative mental repercussions.

Contribution 1: Intelligent Brand Positioning Using Mobile Edge Computing

The use of IoT-enabled devices, IDBP-IoT-MEC may improve biometric authentication and brand value. As a performance benchmark, it examines important metrics such as the equal error rate, false rejection rate, and false acceptance rate. The system's outstanding LINEAR core function feature score is particularly noticeable in its performance on identification tasks.

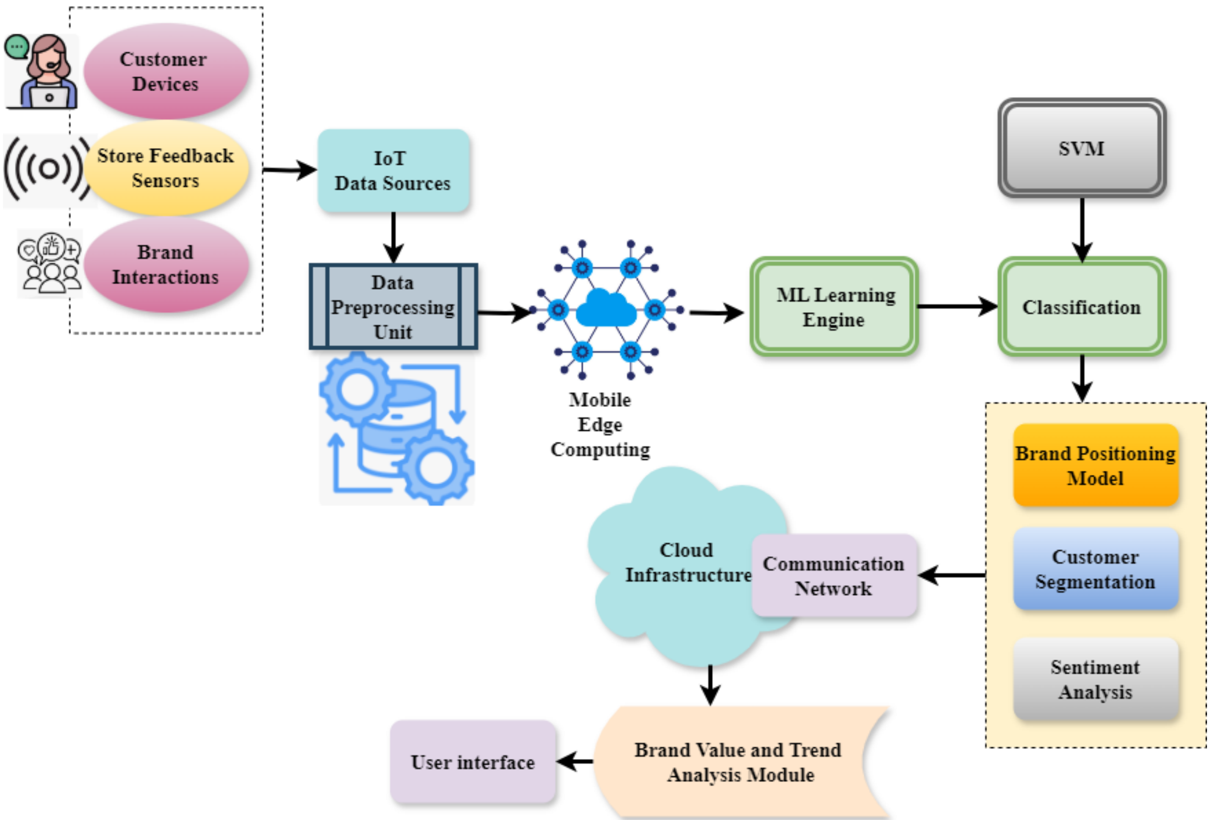

Figure 1: Cosmetics Brand Positioning based on ML in Mobile Edge Networks

Customer devices, in-store feedback sensors, online platforms, and purchasing behavior are the sources of data that an IoT-powered system aims to use to improve brand value analysis and consumer engagement, as explained in Figure 1. A preprocessing unit is utilized to clean, normalize, and aggregate data as it passes through. Edge devices process data specific to stores and mobile apps at the MEC layer, ensuring responses with minimal latency. The ML engine, which includes SVM, powers brand positioning, consumer segmentation, sentiment analysis, and recommendation systems. SVM is particularly effective for classifying consumer sentiments and behaviors, enabling more precise targeting of marketing efforts based on data patterns. Real-time processing is made possible by a communication network optimized for 5G/4G connectivity. Model training and long-term data storage are managed by cloud infrastructure, allowing the system to adapt and maintain accuracy over time. The brand value and trend analysis module provides dynamic scorecards and product trend projections based on insights derived from the results. A user-friendly interface is designed to make this information accessible to managers, marketing teams, and consumers. By employing adaptive learning models, including SVM, and incorporating real-time user input, the system's feedback loop ensures ongoing improvement, further enhancing brand value analysis and consumer engagement.

$$h(+\forall) * \sigma(y) * ez + h(-\rho\tau) = r(y) * ew \quad (1)$$

Within a MEC system, equation 1 depicts the ever-changing connection $h(+\forall)$ between signals related to consumer behavior $(\sigma(y))$ and modifications to brand positioning $(h(-\rho\tau))$. The equation ew represent time-related elements that impact reaction tactics, whereas the terms ez and $h(+\forall)$ represent the exponential impacts. This Equation 1 accurately measures the impact of real-time IoT data on brand strategies, which is the suggested IDBP-IoT-MEC technique.

$$v''(u-1) + e^3 p(v) - H\big(p(k)\big) = r(s), \qquad m(0) = v(2\forall) = 0 \quad (2)$$

The equation 2 represents the change in consumer engagement $(v''(u-1))$ in reaction to personalized marketing $e^3 p(v)$ and past trends $(H\big(p(k)\big))$. The initial product assessments and universal market saturation points $r(s)$ are represented by boundary conditions $m(0)$ and $v(2\forall)$, respectively. This guarantees optimization with the consumer in mind by recording the constant, real-time adjustment of brand value.

$$k_t(u-1) = -\frac{1}{2r} * K\cos(v\forall) + \partial_t(\delta) - \sin(b\delta) * (\nabla \mathrm{f}) \quad (3)$$

Equation 3 represents the dynamic shifts in brand positioning $(k_t(u-1))$ as a function of consumer sentiment $(K\cos(v\forall) +)$ and competitive market forces $(\frac{1}{2r})$. The time-sensitive changes in marketing tactics are represented by the term $(\nabla \mathrm{f})$, while the nonlinear impacts of changes in brand perception $\sin(b\delta)$ are captured by the term $\partial_t(\delta)$. By adapting brand positioning in real-time based on customer and market data, this fits in with the suggested approach.

$$M_t(uv - 2r) = \frac{t}{r} * \cos(ru) + C_d(u2t') \quad (4)$$

This model describes C_d time-sensitive marketing initiatives (M_t) affect both brand positioning and customer perception $(uv - 2r)$. The periodic impacts of focused ads are represented by the term $\frac{t}{r}$, while consumer-driven modifications $u2t'$ based on developing preferences are captured by $\cos(ru)$. This suggested approach demonstrates in equation 4 AI-driven tactics and real-time data constantly alter brand positioning to boost competitive advantage.

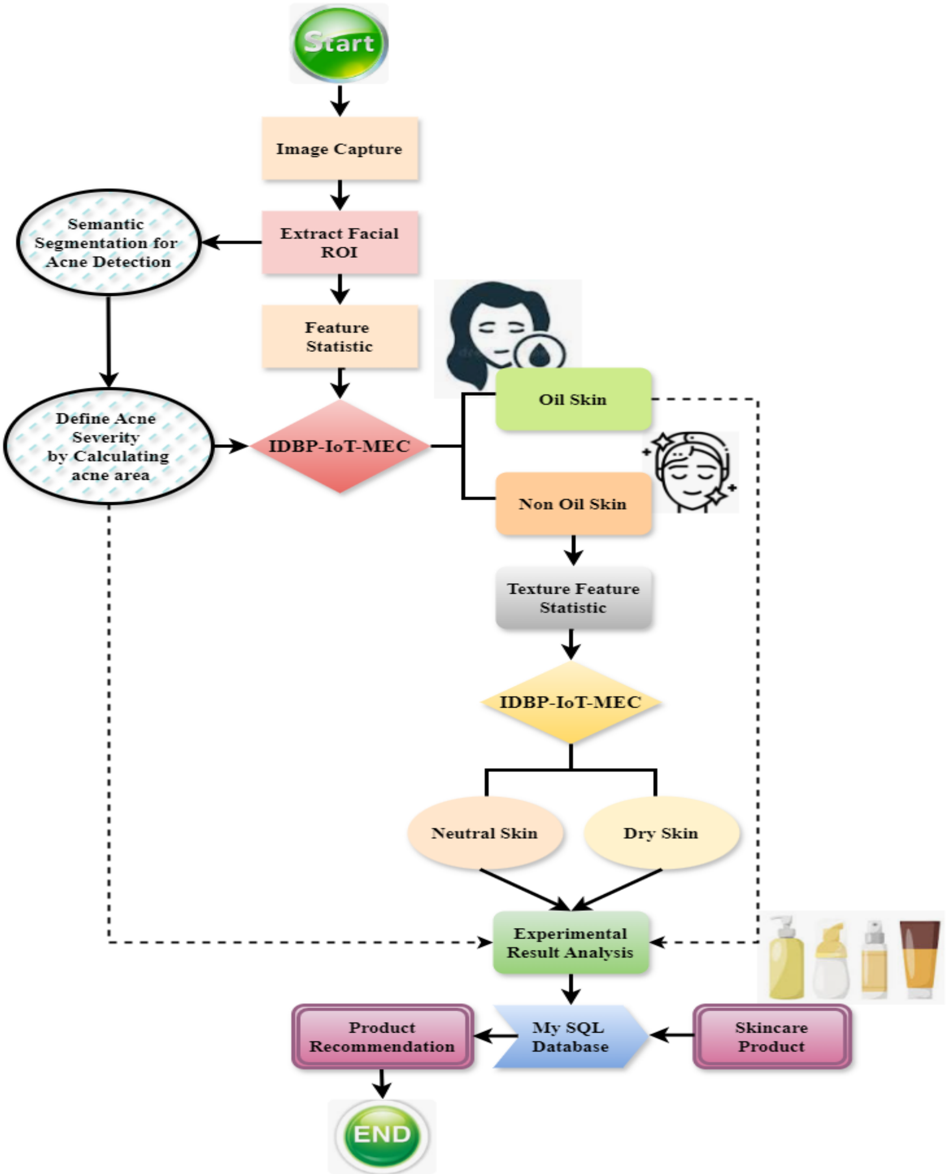

Figure 2: The skincare product suggestion system's flowchart

A well-established supervised learning approach is IDBP-IoT-MEC. It can get experimental data on the false acceptance rate and the false rejection rate with various thresholds once IDBP-IoT-MEC prediction is done. The receiver operating characteristic curve is a linear graph that displays the data points. At some point, the data represent the identical error rate because the FAR and FRR curves meet. The impact of finger-vein identification may be measured using EER. Compared to other ways, this system's feature score of the LINEAR core function is greater. The identification result performed by the LINEAR core function is therefore superior. Two sections make up the skincare product suggestion system: skin type classification and acne detection. A combination of multi-feature processing, ML classification with SVM, and DL semantic segmentation technologies allows for its implementation. Last but not least, customers get face skincare recommendations based on their skin type and acne history. Figure 2 shows a flow diagram of the skincare products' recommendation system.

$$y_t(\partial \pm \forall) = \frac{(-2)e^{k-2}}{ur} * (\tan(\varphi\tau) * Qe - \cos(\mu\vartheta)) \quad (5)$$

The equation 5 represents the time-dependent changes $(-2)e^{k-2}$ in customer engagement $y_t(\partial \pm \forall)$about brand positioning initiatives. The effect of targeted marketing Qe and variations in customer sentiment are captured by the exponential terms $\tan(\varphi\tau)$ and $\cos(\mu\vartheta)$, whilst the fast changes in market perception. Because it measures the impact of real-time data insights on adaptive marketing approaches in a cutthroat market.

$$\tan(\partial\sigma) * H\big(M_w(\omega - 2r)\big) * \rho w \rightarrow H(\pi - \mu) \quad (6)$$

Market dynamics $\tan(\partial\sigma)$ and brand response tactics (M_w) interact in real-time, as shown by the equation 6. While $\omega - 2r$ measures the effect of competing variables $(\pi - \mu)$ on brand positioning ρw, the term H describes changes in customer sentiment. Equation 6 demonstrates MEC system might use analytics powered by SVM.

$$H(p - z) * R(y \pm vf) = Ky\big(m - Z(pt - 2)\big) \quad (7)$$

This equation 7 represents the dynamic interaction $H(p - z)$ in the market between product positioning $R(y \pm vf)$ and customer reactions Ky. The term $m - Z$ represents the time-dependent impact of market trends $(pt - 2)$ and promotional activities. This shows AI-driven tools adapt to changes in real-time, which is with the recommended technique.

Psoducode for Function to handle dynamic brand positioning

```
function IntelligentDynamicBrandPositioning():

   Initialize_IoT_Devices()

   Initialize_Edge_Network()

   consumer_data = Collect_ConsumerData_From_IoT()

   social_media_data = Collect_SocialMediaData()

   sales_data = Collect_SalesData()

   competitor_data = Collect_CompetitorData()

   cleaned_data = Preprocess_Data(consumer_data, social_media_data, sales_data, competitor_data)

   features = Feature_Engineering(cleaned_data)

   model = Train_Model(features)

   real_time_data = Get_RealTimeData_From_Edge_Network()

   prediction = Predict_Brand_Performance(model, real_time_data)

   dynamic_positioning = Analyze_BrandPosition(prediction)

   Adjust_Marketing_Strategy(dynamic_positioning)

   feedback = Collect_RealTimeFeedback()
```

Update_Model(feedback)

The IoT and edge computing environments needed to collect information about consumers and markets in real-time are initialized using the Intelligent dynamic brand positioning function. This function predicts the success of a brand on the basis of machine learning algorithms applied to this information and revises the advertising methods used for the brand based on forecasted performance. It also captures the changes in the IoT environment' and refines the positioning of the brand spread in the environment in question.

Improving real-time brand analysis, it uses IoT data streams and edge computing. Model training on the cloud enables continuous development, and feedback loops guarantee accuracy and flexibility.

Contribution 2: AI-Driven Consumer Behavior Analytics:

To provide safe, individualised services, this project combines a system for identifying finger veins, another system for recommending skincare products, and an electronic payment system. For secure, contactless biometric identification, the fingerprint-vein recognition system is the way to go.

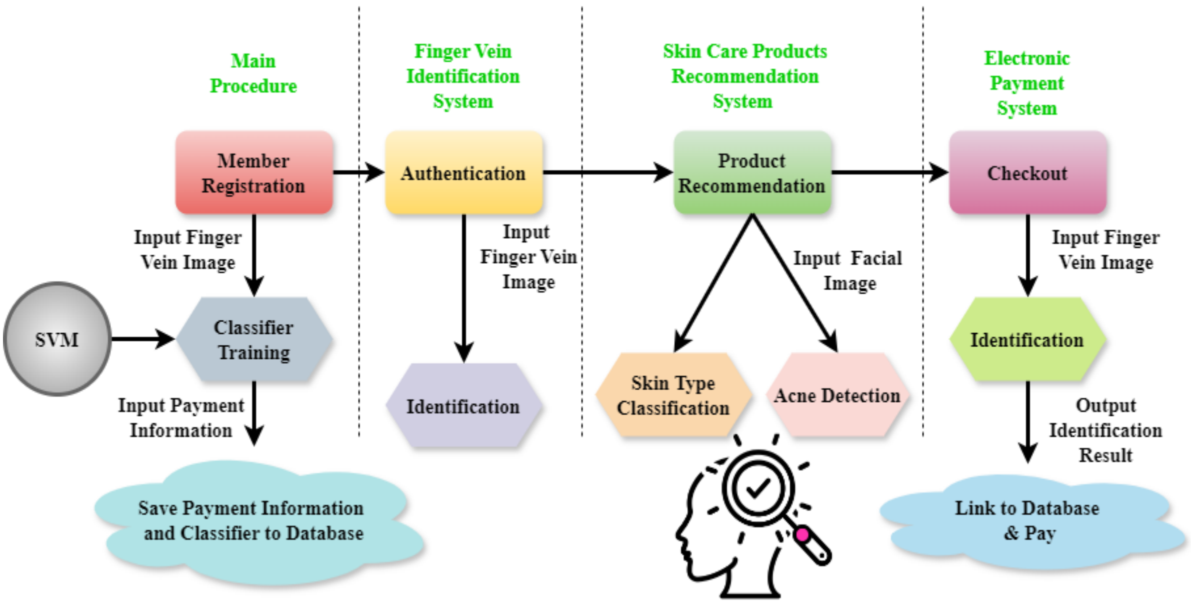

Figure 3: Design of fingerprint-vein identification using SVM

Figure 3 shows the main components of this work's architecture, which include a system for detecting veins in the fingers, another system for making skincare product recommendations, and an electronic payment system. The fingerprint-vein recognition system is the first subsystem that deals with identity verification and personalised service supply. This component uses support vector machines (SVMs) to accurately verify identities by classifying and improving the detection of vein patterns. This is an electronic payment system that utilises member data to generate follow-the-money links and accepts a variety of payment methods. An better user experience is achieved by meeting the criteria of cleanliness, real-time processing, and precision using contactless, quick, and reliable fingerprint-vein recognition technology that is coupled with SVM for increased accuracy. A shadow is created when near-infrared light (NIR) is exposed to haemoglobin in venous red blood cells. With this idea, we can train the identification system to identify veins using near-infrared pictures. To further optimise efficiency in identity verification, SVM is used to categorise and analyse these photos.

$$H(-\forall r) < q' : \frac{1}{Uq} * R(u - \forall) * Rj < H(-\forall \partial r) \quad (8)$$

In response to marketing initiatives $H(-\forall r)$, equation 8 describes the threshold-based link q' changes in brand positioning ($\frac{1}{Uq}$) and the strength of customer reaction $R(u-\forall)$). The Rj denotes the reaction from competitors, whereas $H(-\forall\partial r)$ depicts the restrictions of resources. The MEC system dynamically balances marketing efforts against customer feedback and competition forces using AI is in line with the suggested technique.

$$F(z) \leq q - w \leq h(-t) \quad v \leq T_0 + T_1 \quad (9)$$

Brand positioning efforts are represented by equation 9 which represents the customer traits ($F(z) \leq q$) and their response ($q-w$).

$$(y, z) \rightarrow \left(R_{yz}(U), v'_{yz}(Mp - er) - 2wq\right) \quad (10)$$

Brand positioning efforts are represented by the equation 10 that represents the interaction between customer traits ((y,z)) and their response ($R_{yz}(U)$). This term, which is adjusted for competitive dynamics $2wq$, represents the effect of marketing pressure ((Mp) and external variables (v'_{yz}) on customer behavior ($Mp-er$).

$$\partial(y, wq) \coloneqq \left(z - v' * yz\,(Ux - 2r)\right) - M * (yt) - Z \quad (11)$$

Brand positioning ($\partial(y,wq)$) and the impact of market dynamics $Ux-2r$ are modelled by the equation 11, which Z accounts for changes in consumer behavior $z-v'$. Brand perception by the term yz user experience ($M*(yt)$) and competitive adjustments, while temporal and external aspects are accounted. By showing how the MEC framework's real-time data analytics adaptively fine-tune brand tactics.

<u>Psoducode for Function to initialize IoT devices for consumer data collection</u>

```
function Initialize_IoT_Devices():

    Connect_To_IoT_Sensors()

    Configure_Data_Collection_Protocols()

function Initialize_Edge_Network():

    Setup_Edge_Compute_Resources()

    Establish_Low_Latency_Networks()

function Collect_ConsumerData_From_IoT():

    return IoT_Sensor_Readings()

function Collect_SocialMediaData():

    return Fetch_SocialMedia_Trends()

function Collect_SalesData():
```

The function Collect_SalesData is used to pull the sales data from the live database of the company. It is focused on ensuring the information is up-to-date sales activity and performance figures which are important in working on brand positioning and consumer behavior. This information will help in making the right decisions in marketing and management of sales inventory.

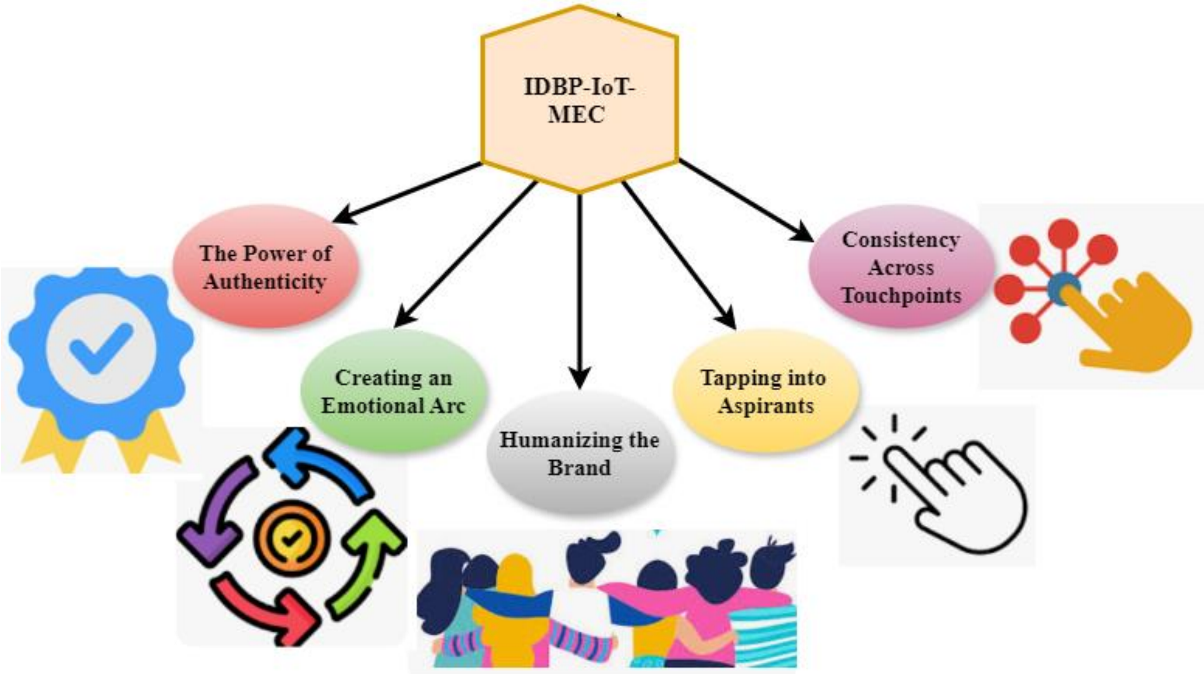

Figure 4: Brand recognition by essential factor

Figure 4 depicts a strategy for enhancing brand awareness via the emphasis on crucial elements of customer engagement. The core principle of this approach, which is called "humanising the brand," highlights the need of establishing an emotional connection with customers. The use of an emotional arc, which allows customers to form a deeper connection with the brand via stories and experiences that resonate with their emotions, and the power of authenticity, which encourages trust and loyalty.

$$Z''_{pk}(m' - u'') \coloneqq (A + B''_{yz} - P[Z_{wq} * (Pz)]Et(v - 2r) \quad (12)$$

The impact of client involvement (Z''_{pk}) on the dynamics of the brand $m' - u''$ as impacted by different circumstances $Et(v - 2r)$ is represented by equation 12. Foundational and dynamic brand qualities are denoted by $A + B''_{yz}$, respectively, while the interplay between promotional techniques and market forces is captured by $P[Z_{wq} * (Pz)]$. The suggested approach, which takes into account intricate customer behaviors and competitive environments.

$$||V_{pk}(u) - y|M_w = Z_r - (m'(U)) * Kp = Hr(v'(Ux)) \leq 0 \quad (13)$$

Equation 13 illustrates the connection between brand positioning Kp and customer happiness $Hr(v'(Ux))$ as measured by the difference between $V_{pk}(u) - y$ and $M_w = Z_r$. The $(m'(U))$ measures the departure from intended results. It fits together to keep customers engaged and successfully satisfy market expectations.

$$H_z \coloneqq Mp(Ty(v' - rG)) * N(Rz_2 + Vh(p' - zw)) \quad (14)$$

To find the brand's efficacy, the equation 14 describes the interplay $Ty(v' - rG)$ between promotional pressure (Mp) and changes in customer behavior (H_z). In response to promotional techniques, the phrase $z_2 + Vh(p' - zw)$

encompasses both network effects N and perceptions motivated by value. In turn, this connects to better marketing tactics that increase engagement and value for the company.

$$T \rightarrow \left(H\left(r + R\left(K_{m-2}^{p}\right)\right) - Y(Z' - Xy)\right) * \partial r(m^2 + Ry) \quad (15)$$

To simulate the transformational impact H of brand strategies (T) on customer engagement $r + R\left(K_{m-2}^{p}\right)$, the equation 15 takes market dynamics and consumer reactions. While $Y(Z' - Xy)$ represents variations in customer happiness, the term ∂r represents brand positioning $m^2 + Ry$ affected by market forces. These market circumstances and real-time input from consumers guarantee that the brand remains effective and relevant.

Algorithm for Brand positioning using SVM

import numpy as np

from sklearn.svm import SVC, SVR

from sklearn.model_selection import train_test_split, cross_val_score

from sklearn.preprocessing import StandardScaler

from sklearn.metrics import accuracy_score, mean_squared_error, r2_score

Step 1: Data Preprocessing

X_cust: Customer data features

X_prod: Product data features

X_market: Market data features

X_sentiment: Sentiment data features

y_class: Brand positioning labels (high, mid, low)

y_value: Brand value score (continuous)

Combine all feature sets

X = np.hstack((X_cust, X_prod, X_market, X_sentiment))

Step 2: Feature Scaling

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)

Step 3: Split Data into Train and Test Sets

X_train, X_test, y_class_train, y_class_test, y_value_train, y_value_test = train_test_split(

```
    X_scaled, y_class, y_value, test_size=0.3, random_state=42
)
```

Step 4: Train SVM for Brand Positioning (Classification)

```
svm_classifier = SVC(kernel='linear', C=1.0)  # Support Vector Classification
svm_classifier.fit(X_train, y_class_train)
```

Step 5: Evaluate the SVM Classifier

```
y_class_pred = svm_classifier.predict(X_test)
accuracy = accuracy_score(y_class_test, y_class_pred)
print(f'Classification Accuracy: {accuracy * 100:.2f}%')
```

Step 6: Train SVR for Brand Value Assessment (Regression)

```
svr_model = SVR(kernel='linear', C=1.0)  # Support Vector Regression
svr_model.fit(X_train, y_value_train)
```

Step 7: Predict Brand Value

```
y_value_pred = svr_model.predict(X_test)
```

Step 8: Evaluate the SVR Model

```
mse = mean_squared_error(y_value_test, y_value_pred)
r2 = r2_score(y_value_test, y_value_pred)
print(f'Mean Squared Error (MSE): {mse:.2f}')
print(f'R-squared (R²): {r2:.2f}')
```

Step 9: Cross-Validation for Performance Check

```
cross_val_accuracy = cross_val_score(svm_classifier, X_scaled, y_class, cv=5, scoring='accuracy')
print(f'Cross-Validation Accuracy: {cross_val_accuracy.mean() * 100:.2f}%')
cross_val_mse = cross_val_score(svr_model, X_scaled, y_value, cv=5, scoring='neg_mean_squared_error')
print(f'Cross-Validation MSE: {-cross_val_mse.mean():.2f}')
```

The algorithm demonstrates the use of Support Vector Machines (SVM) for cosmetics brand positioning and value assessment. It processes data from various sources like customer behavior, product features, market trends, and sentiment analysis. The data is preprocessed by standardising its dimensions and applying many scales. Support Vector Regression (SVR) is used to determine the brand's worth, and a Support Vector Machine (SVM) classifier is employed to forecast the brand's location (low, mid, high). Precision, MSE, and R-squared are the metrics used to measure the model's efficacy. The model's dependability is further confirmed via cross-validation. With this method, companies may optimize their brand strategy by analyzing data in real-time.

The architecture enhances the user experience with contactless fingerprint-vein technology that meets real-time accuracy and cleanliness standards. Vein patterns are photographed using near-infrared (NIR) light for precise identification. The electronic payment system provides convenient payment options based on membership data, guaranteeing hassle-free transactions.

Contribution 3: Efficient Product Efficacy Evaluation Methodology

Innovation, product refinement, and improved brand positioning are all greatly aided by the process of using real-time analytics and data on customer behaviour. Businesses may learn a lot about customer tastes and industry tendencies by using ML to analyse large amounts of data. Future product iterations, advertising campaigns, and even brand positioning can all benefit from this data-driven approach.

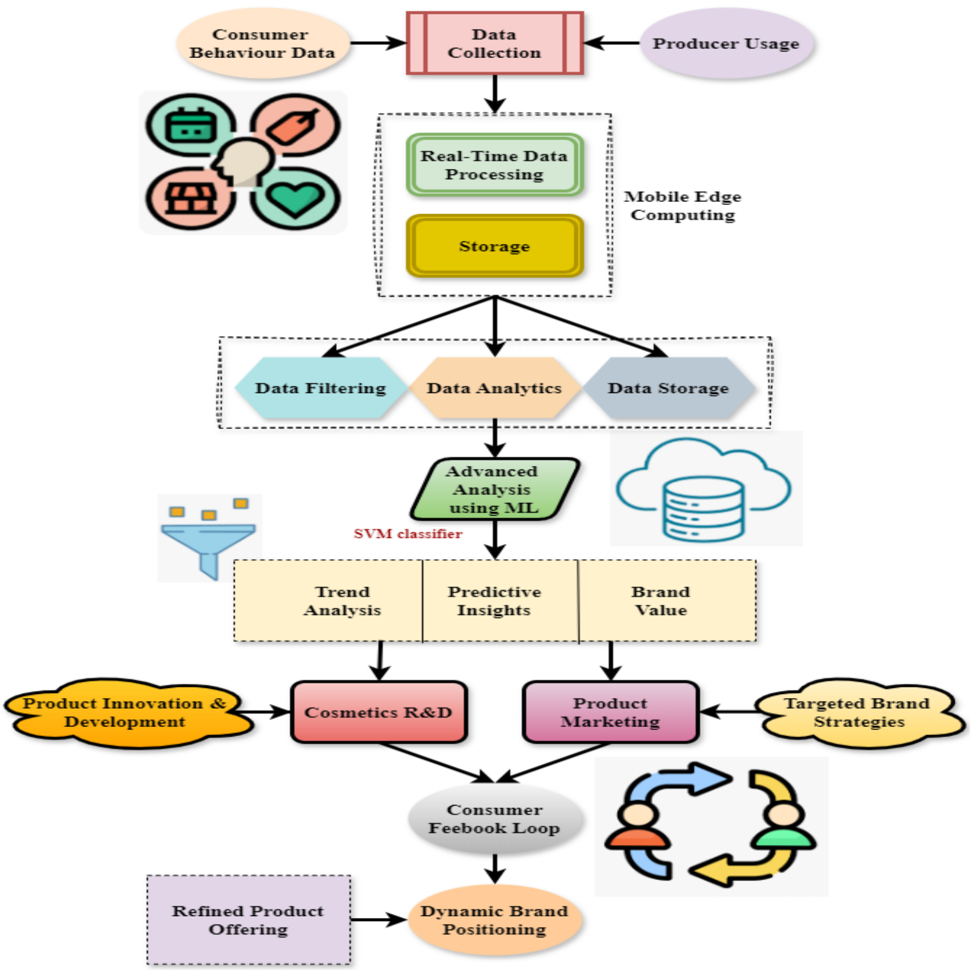

Figure 5: Proposed method of IDBP-IoT-MEC

Figure 5, shows a thorough procedure for driving product development, marketing tactics, and brand positioning using data on customer behaviour and real-time data processing. There is real-time data collection, processing, storage, and filtering of consumer behaviour for further study. Derive forecast insights, analyse trends, and measure brand value using advanced data analytics that use machine learning with SVM. Cosmetics research and development, targeted marketing, and product innovation and development are the corporate areas that benefit from the outcomes. The feedback loop between consumers and businesses allows for ever-changing brand positioning and product offers, which in turn drives marketing and product development efforts. Brand positioning and tactics are fine-tuned in response to customer demands as a result of trend analysis and predictive insights. By coordinating product and marketing efforts with customer tastes, this all-encompassing strategy boosts brand value and guarantees success.

$$E(y, r, T) \coloneqq \big(H(z - T(n * \ z_2 l)wq)\big) * R\big(v(2, r)\big) \quad (16)$$

The model predicts $z - T$ well brand tactics work by connecting market dynamics to customer involvement, which is represented by $E(y, r, T)$. The expression $(n * \ z_2 l)wq$ represents the reaction of consumers $R\big(v(2, r)\big)$ as a result of changes to the brand and real-time data. Brands can better understand customer behaviour, which improves their strategy and analysis of consumer behavior insights effectively in a competitive marketplace on equation 16.

$$v''(u - 2r) = T\left[Q\left(tp + \frac{e}{Dt} * \ \partial Z(b' - ma)\right)\right] \quad (17)$$

External influences $v''(u - 2r)$ and marketing activities Q are modeled by the equation as accelerating consumer engagement (T). The promotional techniques and real-time data modifications' $\partial Z(b' - ma)$ impacts on brand positioning are captured by the term $\frac{e}{Dt}$. That way, firms can adapt to changing market circumstances and customer preferences with ease, with dynamic consumer data on the analysis of dynamic brand positioning in equation 17.

$$B\big(Yz(n' - r)\big) = \frac{1}{qT} * R(v^2 U) - \ C_e(m'yr) \quad (18)$$

Equation 18 represents the connection between several elements $\frac{1}{qT}$ that impact brand performance and the associated equation ($B\big(Yz(n' - r)\big)$). The influence of market dynamics and customer reaction on brand value is captured by the term $R(v^2 U)$, whilst the external expenses associated with marketing activities are accounted for by $C_e(m'yr)$. This framework's AI-driven analytics lets companies measure and optimize their strategy in response to the market in analysis of the efficiency of mobile edge networks.

$$|v'| * (Rf^2 + Mq) = Et - < \forall Q\big(p(k), l'(u)\big) >= 1 \quad (19)$$

The equation 19 between brand response and market pressures, denoted by $Rf^2 + Mq$, is described by $|v'|$. While $|v'|$ represents the average influence of promotional methods on customer behavior, the $< \forall Q(p(k),)$ denotes overall engagement $l'(u)$ or effectiveness. To remain relevant over time, companies must be able to successfully respond to changes in the market and customer tastes on analysis of product efficacy validation.

$$\big||rt'|\big| * \ 20 > \frac{R}{2q}(|Z| * \ d^2 W + \sqrt{U} * |\big|H - T(Yx)\big) \quad (20)$$

Brand influence ($\big||rt'|\big|$) and J^2, which represents the threshold for successful marketing performance, are modeled by the equation 20. By considering brand dynamics $|Z| * \ d^2 W$ and consumer reactions, the term $\frac{R}{2q}$ measures the requisite market conditions $\sqrt{U} * |\big|H - T(Yx)\big)$ for success. In a competitive environment, this connects to achieving optimum engagement and effectiveness on the analysis of synergistic firm-customer interaction.

In result, organizations can acquire significant understanding of consumer habits and trends by using advanced analytics. In addition to driving innovation, targeted marketing, and product enhancement, the feedback loop with clients provides ongoing adaptation. Improvements in competitiveness and brand value are achieved via this process.

4. Result and Discussion:

Improving mobile edge network efficiency, dynamic brand placement, and consumer behaviour analysis are the main areas of attention. Companies may strengthen their relationships with customers, validate the effectiveness of their products better, and get real-time information by using these technologies. Research shows that operational indicators have significantly improved, showing how these innovations generate competitive advantage and elevate overall brand performance.

Dataset Description: Information about cosmetics, such as their brands, names, prices, descriptions, and other properties, is stored in the makeup data file. Insights about product categories, price patterns, and more may be obtained from this dataset, which is a great asset for studying the cosmetics sector and doing market research. Choosing a new cosmetic product is always a challenge for me. Actually, it's not easy at all. It may be nerve-wracking when unfamiliar products produce skin problems. Everything need is on the product's back, but unless a scientist, it's incredibly difficult to understand the component listings [26].

4.1. Analysis of Consumer Behavior Insights:

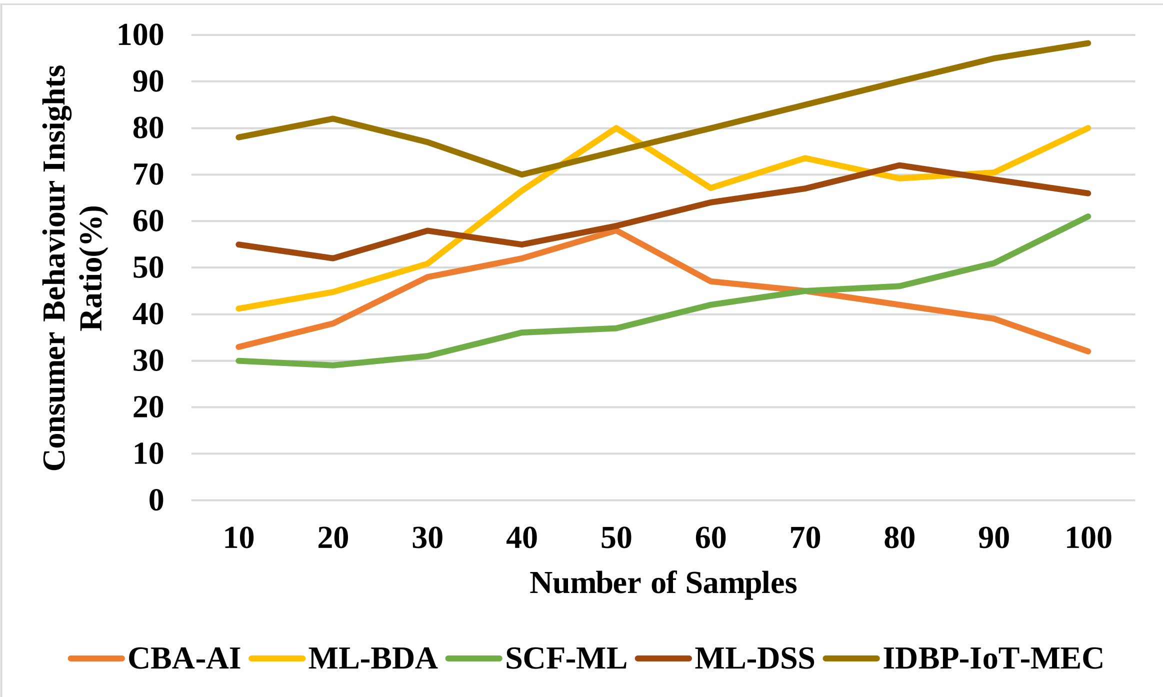

Figure 6: The Analysis of Consumer Behavior Insights

Insights into consumer behaviour are especially important for the cosmetics business when it comes to creating focused marketing strategies and strengthening brand positioning. By analysing massive volumes of consumer data, AI and ML provide potent tools for better understanding consumer tastes, purchasing habits, and emotional reactions. Analytics powered by AI can monitor client activity across all channels, illuminating their wants, requirements, and driving factors in real time is explained in equation 16. Sentiment analysis, and UGC analysis are the system that businesses can employ to provide customers with better tailored experiences, which in turn increases customer happiness and loyalty using SVM. By using data to inform decisions, companies can respond quickly to shifting customer tastes and market conditions, all while honing their products and messaging. Using these insights may give a leg up in a dynamic market and boost the brand's worth. The consumer behaviour insights ratio is improved by 98.24% is shown in figure 6.

4.2. Analysis of Dynamic Brand Positioning:

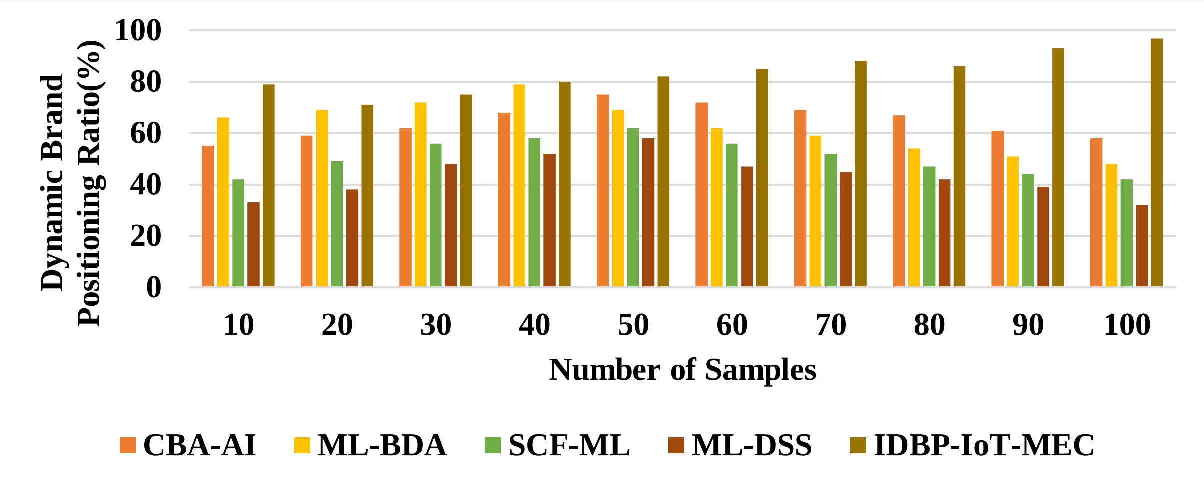

Figure 7: The Graphical Representation of Dynamic Brand Positioning

Dynamic brand positioning is the practice of constant change and reconstruction of the company's identity and message in accordance with the tastes of the clients, the competitive situation, and trends in the market. Nowadays, the development of ultramodern technologies such as mobile edge computing, SVM helps to perform this process much easier. Particularly in sectors like cosmetics, these technologies allow organizations to rapidly change their posture based on real-time data concerning what customers are doing as is explained in equation 17. This includes addressing customers' needs and what the market requires since, with this form of positioning, it is possible for brands to remain relevant while also embracing competition. For example, to keep track of changing customer opinion and market changes, companies can utilize intelligent analytics and internet of things based solutions to ensure that their messages, products and brand attributes are not lost or stray away from the target. These specified technologies also help advance marketing and product development that is most needed in beating the competition in the given market. This strategy fosters long-term profitability in terms of consumer retention and brand equity. In figure 7, the dynamic brand positioning is realized to be achieved in the proposed method of IDBP-IoT-MEC by 96.73% with the collaborative effort of the stakeholders..

4.3. Analysis of Efficiency of Mobile Edge Networks:

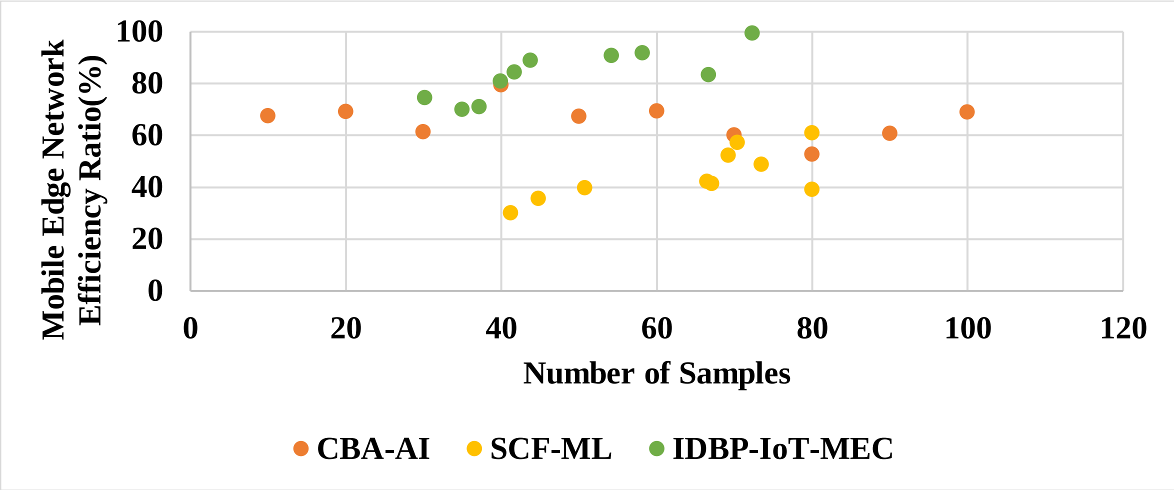

Figure 8: The Graphical Illustration of Efficiency of Mobile Edge Networks

To improve reaction times and decrease latency, MEC bring computing operations closer to the user, which in turn increases data processing efficiency using using SVM. With MEC, IoT-driven industries like smart retail and cosmetics can handle massive amounts of real-time data from linked devices without straining centralised cloud servers. This greatly improves system performance. This closeness to consumers enables quicker, more targeted decisions, which is vital for apps that need quick responses, such as those that monitor customer behaviour or provide personalised product suggestions is derived in equation 18. Network congestion and bandwidth utilisation are minimised via the use of MEC, which enhances system efficiency and scalability by outsourcing complicated activities to edge devices. These tasks may include AI-based analytics or machine learning algorithms. More importantly for sectors focused on customers, MEC improves user experience by delivering services that are quicker and more responsive. Continuous improvements are making MEC a very effective option for boosting overall network performance, but controlling its computational complexity is still a problem, particularly when it comes to incorporating machine learning processes. In the proposed method of IDBP-IoT-MEC the efficiency ratio is gained by 99.41% is shown in figure 8.

4.4. Analysis of Product Efficacy Validation:

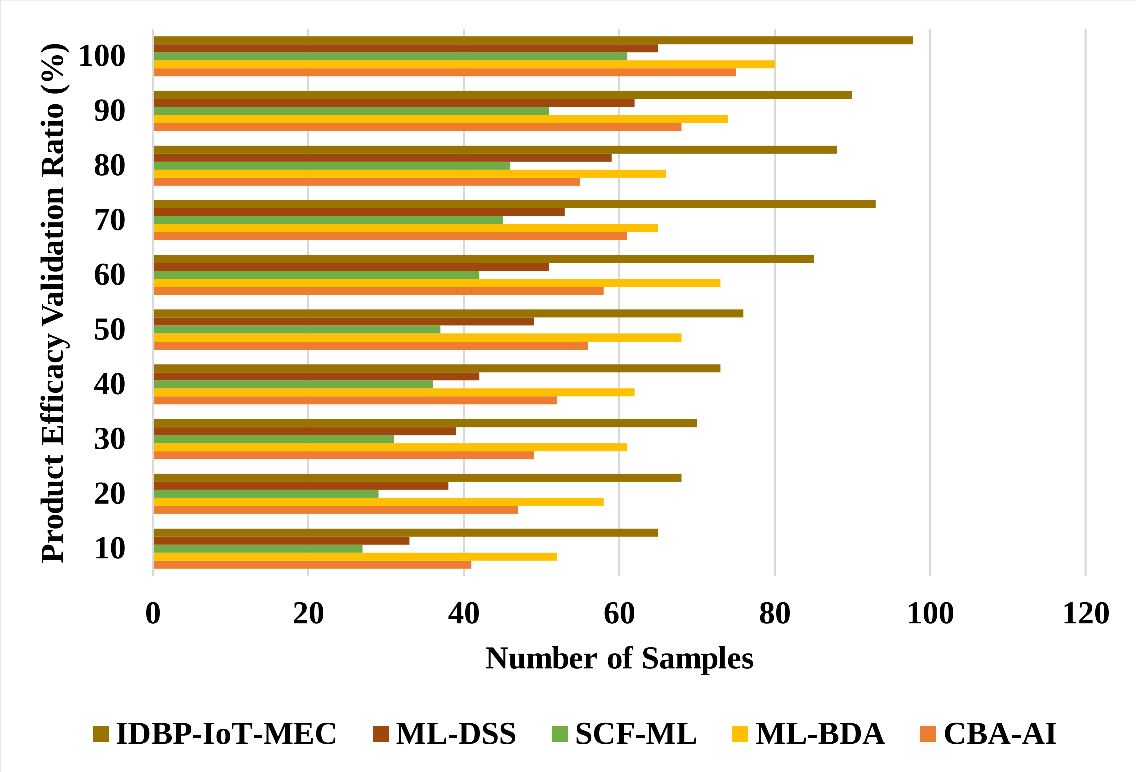

Figure 9: The Analysis of Product Efficacy Validation

Companies in the cosmetics industry, for example, rely heavily on product efficacy validation to win over consumers and government agencies. This is the process of determining, via scientific means, if a product really improves skin texture or diminishes wrinkles, for example. Empirical evidence that backs up marketing claims is provided by methods like consumer testing, clinical studies, and sophisticated data analytics, which are used to confirm effectiveness is explained in equation 19. The validation process is now more dynamic and efficient to the emergence of SVM and IoT technology. To provide real-time insights into product performance, AI-driven solutions may analyse enormous datasets including customer input or lab findings. Furthermore, gadgets that are connected to the internet may track how a product is used over time in real-life settings, providing ongoing data that can be used to improve the recipe. To guaranteeing high-quality goods, effectiveness validation encourages innovation by pushing businesses to create items with shown advantages. In a industry, this increases trust among buyers, which in turn increases rivalry and strengthens the reputation of the brand. The Product efficacy validation is gained by 97.83% is shown in figure 9.

4.5. Analysis of Synergistic Firm-Customer Interaction:

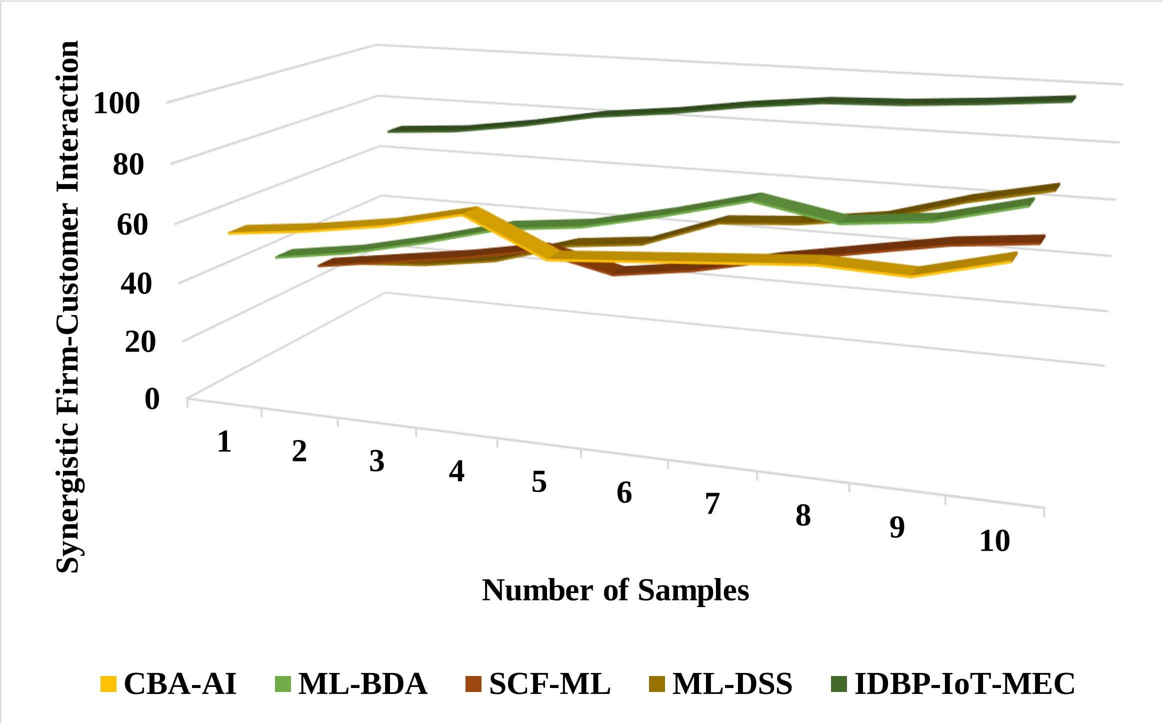

Figure 10: The Graphical Representation of Synergistic Firm-Customer Interaction

In figure 10, this kind of connection where the firm and the customer work together to enhance the development of products, the marketing of the products as well as the experience of the customer as a whole is called synergistic firm-customer interaction. Abundant and advanced technologies including mobile edge computing, the Internet of Things and using SVM all bring about the effect of ensuring that feedback is readily available and engaging in conversations explains the movement outlined in equation 20. Understanding the customers' usage of products is possible through the use of SVM, making it easier to enhance communication and offerings. Feedback from customers, acquired through online surveys, social networks or the IoT, is crucial for improving the level of services and developing the products. This participatory paradigm integrates user contribution in the product development process, hence not only does it promote creativity, it also fosters consumer loyalty. When business and customer interaction is supplemented, a circular feedback system is established which helps in brand enhancement and ensures that both goods and services adapt with the ever-ending ceaseless changes in consumer patterns. The synergistic firm customer interaction is obtained by 96.43% in the proposed method of IDBP-IoT-MEC.

Table 2: Comparision table for findings of the proposed method

S. No	Aspects	Methods	IDBP-IoT-MEC	Ratio (%)
1	Consumer Behavior Insights	ML analysis of consumer data, sentiment analysis, chatbots using SVM	Enhances understanding of consumer preferences, real-time insights, tailored experiences	98.24%
2	Dynamic Brand Positioning	Real-time data analysis using SVM, IoT, mobile edge computing	Allows adaptive brand strategies, aligns with market trends, enhances relevance	96.73%
3	Efficiency of Mobile Edge Networks	Data processing at the edge, SVM -based analytics	Reduces latency, improves response times, lowers network congestion	99.41%

4	Product Efficacy Validation	SVM driven analytics, consumer testing, clinical studies	Provides empirical evidence of product benefits, supports innovation	97.83%
5	Synergistic Firm-Customer Interaction	ML-driven analytics, real-time feedback through IoT and digital channels	Enhances communication, fosters innovation, improves customer loyalty	96.43%

In summary, companies may improve product effectiveness validation, create synergistic relationships with consumers, and acquire real-time data by employing these technologies. Improvements in operational metrics such as network efficiency (99.41%), consumer behaviour insights (98.24 %), dynamic brand positioning (96.73%), product efficacy validation (97.83%), and firm-customer interactions (96.43%) are demonstrated to be substantially enhanced by integrating ML with SVM, the IoT, and mobile edge computing. This method promotes innovation and market competitiveness while simultaneously increasing brand value and consumer happiness.

5. Conclusion:

One important aspect of cosmetic dermatology is the use of machine learning in several roles. The purpose of this IDBP-IoT-MEC compliant systematic literature review was to synthesise the most recent findings from this area of SVM. The papers that were reviewed were divided into five categories based on the duties they were assigned, developing cosmetic products, assessing skin, diagnosing skin conditions, recommending treatments, and predicting treatment outcomes. A emphasis on identifying trends, constraints, and future potential was placed on the use of machine learning technologies in the cosmetic dermatology area. The main thing this paper does is look at current research that have tried to use SVM in cosmetic dermatology and systematically analyses them. This paper will serve as a starting point for future research into the gaps in this area's contributions and as a guide for medical and IT professionals interested in using intelligent technology to cosmetics industry problems. The cosmetics industry stands to gain a great deal from ML's integration with SVM, the Internet of Things (IoT), and mobile edge computing when it comes to brand positioning and new product creation. Smart solutions like IDBP-IoT-MEC may help businesses learn more about consumer habits, validate products more effectively, and create dynamic brand positioning strategies. Innovation, customer delight, and competitiveness are all boosted by these technologies, which provide real-time information and tailored experiences. Customers are more likely to have a great experience and provide a favourable review for a product if it meets their needs. Adopting these technologies may help companies thrive in today's hyperconnected and constantly evolving economy.

Future Work: Future study might focus on enhancing the adaptability and scalability of IDBP systems to various market conditions. Researchers should also investigate data security and privacy concerns to guarantee that technology properly handle sensitive information. Looking at ways to incorporate new technologies, like blockchain to enhance data integrity or augmented reality to provide consumers more immersive experiences, can lead to some innovative ideas. Academics, technology providers, and industry stakeholders must collaborate to stay up with the dynamic digital landscape and capitalise on emerging developments.

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