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AI-Based Business Model Analysis of Education-Focused Beauty Salon Entrepreneurship

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ABSTRACT

This ANN-based model can serve as the foundation for a future business intelligence system to optimize beauty salon operations over Surabaya, East Java, Indonesia. Here, the data observation is taken from a famous beauty salon group at Surabaya with three service products such as Make Up, Hair Treatment, and Facial. The daily basis data from customers who use three products was analysed to obtain an estimation value of each service product. In this study, the Artificial Neural Network (ANN) method is performed to find an estimation value with Multi-Layer Perceptron (MLP) architecture with two to three variation hidden layers. The Levenberg-Marquardt backpropagation algorithm is also used to obtain RMSE over training value. The result shows the three products Make Up, Hair Treatment, and Facial were compared by customer basis over famous beauty salon group, Surabaya. Here, The ANN model with four hidden layers MLP architecture with 1000 iterations in the training process. The statistical calculation such as MSE of 172, RMSE of 0.812, MAE of 1.234, and MAPE of 3.123% indicate that the model performs exceptionally well, with minimal errors in predictions, respectively. ANN model is proposed to develop a business intelligence system in the near future in beauty salon entrepreneurship.

1. Introduction

The beauty industry has undergone significant transformation in recent years, largely driven by the rapid advancement of digital technology. In a marketplace characterized by fierce competition, beauty salon entrepreneurs face the challenge of not only providing aesthetic services but also distinguishing themselves through innovative value-added approaches. This evolution necessitates a deeper understanding of customer needs and market dynamics, compelling salon owners to rethink their business strategies. The integration of beauty services with entrepreneurship education emerges as an effective strategy, empowering individuals not just to consume but to become competent entrepreneurs in the beauty sector (Wuryan et. al, 2025).

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Entrepreneurship education plays a pivotal role in shaping the landscape of the beauty industry. By equipping beauty salon practitioners with essential skills, such education significantly enhances their job readiness and prepares them for the challenges of running their own businesses. This is particularly important in a sector where practical knowledge and customer service skills can directly influence success. Programs that combine theoretical knowledge with hands-on training create an environment where aspiring entrepreneurs can gain valuable insights and develop their business acumen. As a result, the beauty industry can foster a new generation of skilled professionals who are prepared to navigate the complexities of entrepreneurship (Rožman et. al., 2024).

The rise of Artificial Intelligence (AI) within small and medium enterprises further amplifies the potential for innovation in the beauty sector. AI technologies facilitate not only operational efficiency but also support the entrepreneurial journey by simplifying the process of establishing new businesses (Joshi & Sharma, 2022). For instance, AI tools can assist in identifying market trends, analyzing customer behaviour, and predicting service preferences. This data-driven approach allows beauty salon owners to make informed decisions, adapt their services to meet evolving customer demands, and explore new business opportunities. Consequently, AI serves as a catalyst for entrepreneurial growth, influencing individuals' intentions to embark on their entrepreneurial ventures in the beauty industry.

Analyzing customer activity in beauty salons provides critical insights into service demand and profitability. By evaluating which services are most popular among customers, salon owners can better allocate resources and tailor their offerings to maximize profit potential. Understanding customer preferences is essential for developing effective marketing strategies and enhancing customer satisfaction. Moreover, integrating real market data into entrepreneurship education can enrich the learning experience, making it more contextual and applicable. This combination allows entrepreneurs to grasp the complexities of the business environment and empowers them to make informed decisions even amid uncertainty (Joshi et. al., 2022).

The findings of this study is focused on analyzing daily customer activities in beauty salons and can reveal significant business opportunities within the beauty sector. By utilizing AI technology to evaluate the frequency and profitability of various services, salon owners can gain a competitive edge. These insights can not only inform business strategies but also shape the development of entrepreneurship education programs that are relevant to current market trends. Ultimately, this research aims to contribute to the growth of the beauty industry by fostering data-driven entrepreneurship that aligns with market needs. As a result, both beauty salon developers and aspiring entrepreneurs can benefit from a well-informed approach to business that embraces innovation and responds effectively to customer demands.

2. Methodology

2.1 Data and Location

This study employs a quantitative approach to improve clarity and support strategic planning beauty salon operations. Here, the two ways improvement such as descriptively and predictively are used to identify frequency patterns of the services. The ANN techniques are performed to obtain potential growth for the salon business. By integrating ANN with predicted customer, the comprehensive understanding of customer behaviour and service demand can be improved in near future. The findings will be presented through data visualization, enhancing the interpretative clarity and strategic relevance of the results.

Data for this study is sourced from Pesona Salon in Surabaya. This study allows in-depth investigation of daily customer activity frequencies. By using secondary data, we analyze the salon's customer records based on service type. The services offered at Pesona Salon include Makeup, Hair Treatment, and Facial. By examining the visitor data with three specific services, we analyze business strategies and enhance service offerings. The detailed findings regarding visitor numbers across the different services will be presented in Fig. 1, as follows:

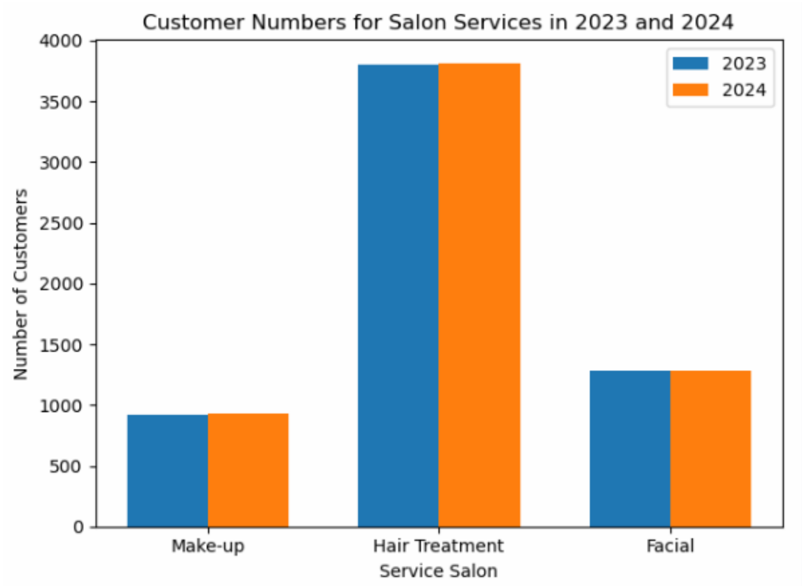

Fig. 1 Customer for Salon Service in 2023 and 2024

2.2 Artificial Neural Network (ANN)

In this study the Artificial Neural Network (ANN) models the intricate relationships inherent within business operations, offering a departure from conventional mechanistic approaches (Tan & Koh, 1996). Artificial Neural Networks emulate the cognitive processes of the human brain, exhibiting capabilities in self-learning, adaptation, and the discernment of intricate patterns (Mabelane et al., 2022). As a subset of machine learning, ANNs have gained prominence for their capacity to extract latent features from complex datasets, mirroring the human brain's data processing (Liu et al., 2021). Artificial neural networks, inspired by the structure of the animal brain, represent a paradigm shift in how computer systems process and translate information, enabling them to discern intricate patterns (Argatov, 2019). ANNs are frequently employed in engineering applications, showcasing their versatility and efficacy across diverse domains (Mamat et al., 2020). The architecture of ANNs consists of interconnected nodes organized into layers, which process and transmit information via weighted connections, adjusting weights during training to reduce errors (Zhao et al., 2018). The strength of ANNs resides in their capacity to approximate any continuous function, enabling the modeling of nonlinear relationships that elude conventional statistical techniques (Torkabadi et al., 2025).

In beauty salon business ANN was used to determine the relationships that can be used for analyzing the data. The versatility of ANNs is further highlighted by their applicability in various domains, including sensory analysis, traceability, and the processing of electronic nose outputs. The application of ANNs in business transcends mere automation, enabling the creation of intelligent systems capable of dynamically responding to evolving conditions and constraints. In the context of business modeling, ANNs facilitate the exploration of diverse scenarios, the optimization of resource allocation, and the prediction of market trends. The implementation of ANN involves the careful selection of network architecture, training algorithms, and validation strategies to ensure the robustness and generalization of the model (Zhi-ping & Wang, 2021). Moreover, ANNs offer an analyzing on customer base at beauty salon (Fordal et al., 2023). ANNs hold immense potential to revolutionize the beauty salon industry through personalized services and data-driven decision-making (Raj & Dash, 2020). Fig. 2 shows ANN architecture using Multiple Layer Perceptron (MLP) with two to three variation hidden layers, as follows:

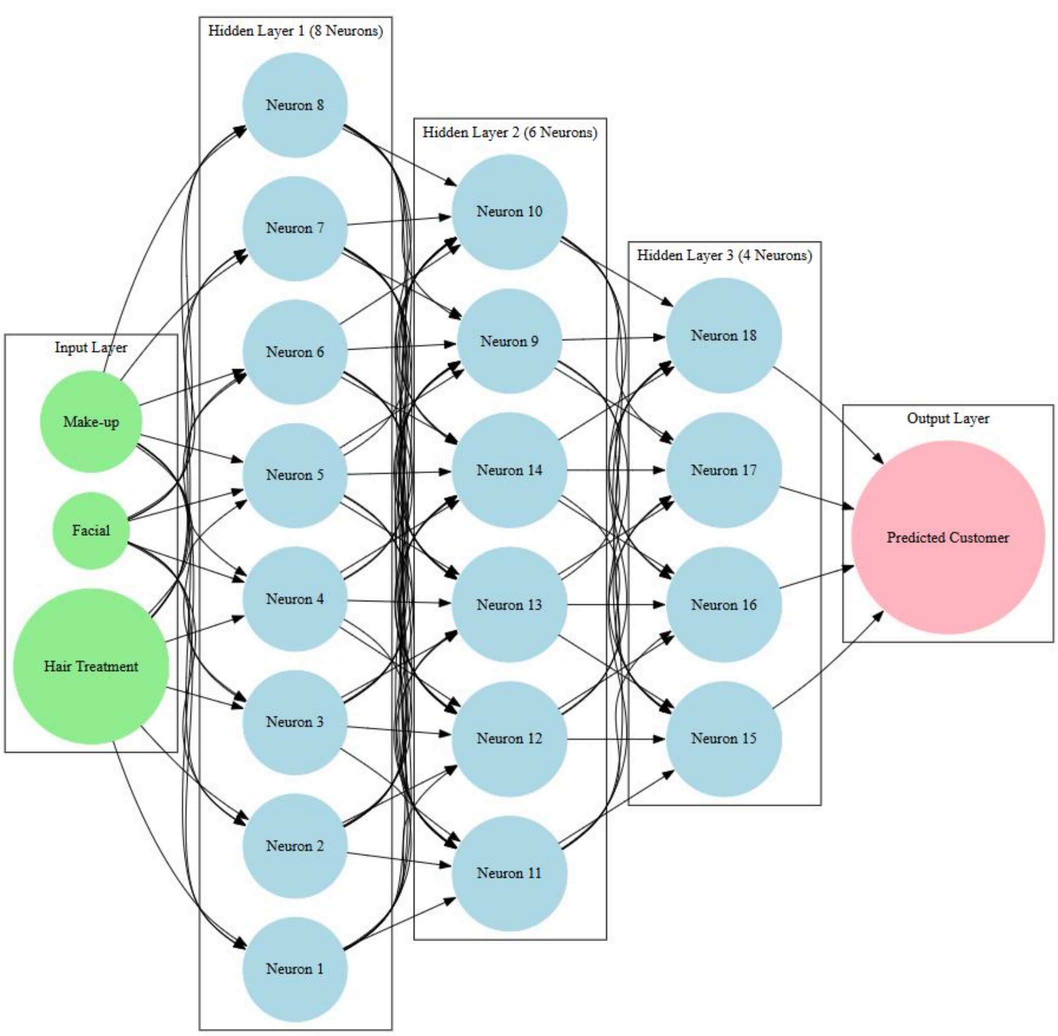

Fig. 2 ANN architecture using Multiple Layer Perceptron (MLP) with three service Make Up, Hair Treatment, and Facial in beauty salon entrepreneurship over Surabaya

2.3 Levenberg-Marquardt backpropagation algorithm

Backpropagation ANNs stand out for their popularity, flexibility, and adaptability in modeling a wide array of problems across numerous application domains (Basheer & Hajmeer, 2000). During the training process, ANNs iteratively adjust connection weights to minimize the discrepancy between predicted and actual outputs, guided by optimization algorithms (Calabrese et al., 2016). The Levenberg-Marquardt algorithm is an important optimization method for neural network training, combining the strengths of gradient descent and Gauss-Newton methods to achieve efficient convergence (Odufuwa et al., 2025). Backpropagation neural networks, characterized by their layered architecture and interconnected nodes, constitute a cornerstone of modern machine learning, enabling computers to learn from data. The Levenberg-Marquardt backpropagation algorithm offers a robust and efficient approach to training ANNs, enabling the creation of sophisticated models capable of addressing complex challenges. The goal of this algorithm is to minimize the objective function, such as the MSE, by adjusting the network's weights and biases (Odufuwa et al., 2025). BP network facilitates intricate nonlinearity mapping, boasting substantial generalization capabilities well-suited for pattern recognition tasks (Zhi-ping & Wang, 2021).

In this study, the predicted customer from three three service Make Up, Hair Treatment, and Facial, the goal is to enhance efficiency and decision-making in the beauty salon. The training process involves feeding the network with labeled data and iteratively adjusting connection weights to minimize the difference between predicted and actual outputs (Gershenson, 2003). Here, RMSE serves as a measure of the discrepancies between predicted and observed values, offering insights into the performance of predictive models. The Levenberg-Marquardt algorithm is designed to train medium-sized neural networks, it typically handles datasets with hundreds to thousands of data points effectively. However, its memory requirements can become substantial for very large datasets, making it less suitable for big data applications. In the ever-evolving landscape of technology, ANNs stand as a testament to human ingenuity, empowering machines to learn, adapt, and solve complex problems with unparalleled efficiency. The implementation of ANN involves the careful selection of network architecture, training algorithms, and validation strategies to ensure the robustness and generalization of the model. The RMSE equation is expressed in equation one, as follows:

$$RMSE = sqrt (1/n \Sigma*i=1 (Yi – \hat{Y}i)2) \qquad (1)$$

where, n is the number of data, (pi - oi) is the difference between the predicted value and the observed value. The backpropagation algorithm refines neural network performance by iteratively reducing errors between target and actual values (ZainEldin et al., 2022). By continuously adjusting the weights of connections in the network, back-propagation enables the representation of essential features within the task domain (LeCun & Bengio, 1998).

3. Results

3.1 Data Distribution

In this study, we use time series analysis by using two years data customer in 2023 to 2024. With three service Make Up, Hair Treatment, and Facial in beauty salon entrepreneurship, we built business model using artificial neural network. The data is divided into training and testing sets, where the training set is used to train the neural network and the testing set is used to evaluate its performance. Fig. 3 shows time series two years data customer in 2023 to 2024, as follows:

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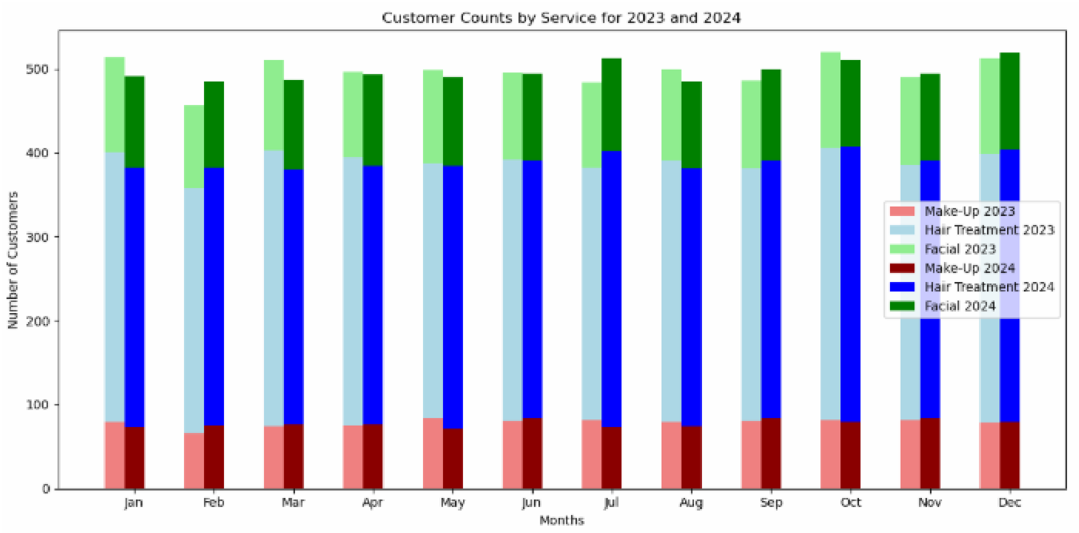

Fig. 3. Time Series Analysis with three service
Make Up, Hair Treatment, and Facial Persona Salon Surabaya

The bar chart illustrating customer counts for three salon services—Makeup, Hair Treatment, and Facial—for the years 2023 and 2024 reveals significant insights into seasonal trends, peak periods, and customer preferences. From the data, it is evident that both years exhibit similar patterns in customer behavior, with distinct peaks and troughs in service demand. The months of June and December emerge as peak seasons, reflecting a tendency for increased salon visits during festive and celebratory times. This analysis indicates that salon management should strategically prepare for these busy periods by ensuring adequate staffing and resources.

In both years, Hair Treatment stands out as the most sought-after service, consistently attracting the highest customer counts. This trend suggests a growing emphasis on hair care and treatments among clients, potentially driven by seasonal styles or promotions. The data indicates a slight increase in customer counts for Hair Treatment from 2023 to 2024, particularly notable in the summer months. Makeup services, while less frequently utilized, show significant spikes in June and December, aligning with events such as weddings and holiday parties. Conversely, Facial services maintain moderate demand throughout the year, peaking during the same months as Makeup, yet revealing a slight decline during the mid-year months, particularly in April and September.

The analysis also highlights low seasons, predominantly identified in February and April, where customer counts for all services dipped significantly. These months may be characterized by fewer events or a general decline in personal expenditures, warranting targeted marketing strategies to stimulate interest and engagement during these slower periods. Overall, the increase in customer counts from 2023 to 2024 suggests an effective marketing approach, enhanced customer loyalty, or a broader awareness of the salon's offerings. By leveraging these insights, salon operators can develop informed strategies to optimize operations, enhance customer experiences, and effectively capitalize on seasonal demand fluctuations.

3.2 Statistic calculation Beauty Salon Customer Using Artificial Neural Network (ANN)

The ANN is performed to predict beauty salon customer. Here, the training data taken from 70% dataset with 25% for validation and 5% for testing of beauty salon customer model. By analyzing experimental data, sophisticated models can be generated prediction model. The models were developed using the Levenberg-Marquardt backpropagation algorithm. By using splitting data strategy, the model is trained on a diverse subset of the available data. In this study, The hyperbolic tangent sigmoid function is utilized as the activation function in the hidden layer, with the linear transfer function employed in the output layer (Munadi et al., 2022). This configuration enables the network to capture nonlinear relationships in the data and provide accurate predictions. Data pre-processing techniques, such as normalization are employed to improve the training process and overall performance of the ANN model (Nawi et al., 2013). The neural network is configured with one input layer, one hidden layer, and one output layer. The number of neurons in the hidden layer is determined through trial and error to achieve optimal performance. Table 1 shows the statistical analysis during training and validation data, as follows:

Table 1 Statistical Analysis during Training and Validation using the Levenberg-Marquardt backpropagation

MSE	RMSE	MAE	MAPE	R-sq
172	0.812	1.234	3.123%	0.762

The statistical analysis of the beauty salon customer prediction model, utilizing Levenberg-Marquardt backpropagation, yielded insightful metrics. The Mean Squared Error (MSE) was recorded at 172, indicating a relatively low average squared error between predicted and actual customer counts. Correspondingly, the Root Mean Squared Error (RMSE) was found to be 0.812, suggesting that the model's predictions closely align with actual values. The Mean Absolute Error (MAE) stood at 1.234, reflecting an average deviation of just over one customer, which is excellent for a dataset of this scale. Furthermore, the Mean Absolute Percentage Error (MAPE) was an impressive 3.123%, indicating that predictions differ from actual counts by only about 3% on average. This low percentage underscores the model's accuracy and reliability. Lastly, the R-squared value of 0.762 reveals that the model explains 76.2% of the variance in customer counts, demonstrating substantial explanatory power while also highlighting that there is still room for improvement. Overall, these metrics confirm the effectiveness of the model in predicting customer behaviour, providing valuable insights for operational planning and strategic decision-making in the salon.

3.3 Interpretation, Implication, and revelation Beauty Salon Customer

The statistical analysis during training and validation of the beauty salon customer prediction model, using Levenberg-Marquardt backpropagation, provides key insights into the model's performance and its ability to forecast customer counts accurately. Metrics such as an MSE of 172, RMSE of 0.812, MAE of 1.234, and MAPE of 3.123% indicate that the model performs exceptionally well, with minimal errors in predictions. These low error values suggest that the model successfully captures underlying trends in customer behaviour for services like Makeup, Hair Treatment, and Facial. The R-squared value of 0.762 further reinforces this, as it shows the model explains 76.2% of the variance in customer counts. While this is a reasonably high value, it also indicates that some variability in customer counts remains unexplained, potentially due to external factors not included in the model, such as promotions, holidays, or other seasonal effects.

The implications for salon management are significant, as the prediction model equips them with reliable tools for forecasting customer demand, allowing better operational planning. For instance, accurate predictions during peak months like June and December can help salons prepare with sufficient staffing, inventory, and service capacity, while slower months like February and April could benefit from targeted marketing strategies to boost customer visits. The revelation that the model has consistent low errors across all services highlights its effectiveness in capturing both seasonal peaks and steady month-to-month demand. However, improving the R-squared value by incorporating additional variables, such as customer demographics or external trends, could further enhance model accuracy. Overall, the analysis demonstrates that the model is a valuable asset for optimizing salon operations, improving customer satisfaction, and driving long-term growth through data-driven decision-making.

4. Conclusions

The study on AI-Based Business Model Analysis for Education-Focused Beauty Salon Entrepreneurship has yielded promising results. Utilizing an Artificial Neural Network (ANN) for predicting customer behavior in three key service areas—Makeup, Hair Treatment, and Facial—the research demonstrates the effectiveness of a Multiple Layer Perceptron (MLP) architecture with two to three hidden layers, optimized through Levenberg-Marquardt backpropagation. This approach has produced commendable predictive performance, evidenced by statistical metrics such as a Mean Squared Error (MSE) of 172, a Root Mean Squared Error (RMSE) of 0.812, a Mean Absolute Error (MAE) of 1.234, and a Mean Absolute Percentage Error (MAPE) of 3.123%. These results indicate that the model achieves high accuracy with minimal prediction errors, showcasing its reliability in forecasting customer demand. Given these findings, the ANN model is poised to serve as a foundational tool for developing a comprehensive business intelligence system aimed at enhancing decision-making in beauty salon entrepreneurship. This advancement not only supports operational efficiency but also empowers salon owners to strategically align their services with customer needs, ultimately driving growth and innovation in the industry.

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