# Machine Learning for Exhibition Recommendation in a Museum's Virtual Tour Application

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***Abstract*—The museum visit is having a crisis during the COVID-19 pandemic. SMBII Museum in Palembang has a remarkable decrease of visitors up to 90%. A strategy is needed to increase museum visits and enable educational and tourism roles in a pandemic situation. This paper evaluates the machine learning model for exhibition recommendations given to visitors through virtual tour applications. Exploring unfamiliar museum exhibitions to visitors through virtual museum applications will be tedious. If virtual collections are ancient and do not display any interest, they will quickly lead to boredom and reluctance to explore virtual museums. For this reason, an effective method is needed to provide suggestions or recommendations that meet the interests of visitors based on the profiles of museum visitors, making it easier for visitors to find exciting exhibition rooms for learning and tourism. Machine learning has proven its effectiveness for predictions and recommendations. This study evaluates several machine learning classifiers for exhibition recommendations and development of virtual tour applications that applied machine learning classifiers with the best performance based on the model evaluation. The experimental results show that the KNN model performs best for exhibition recommendations with cross-validation accuracy = 89.09% and F-Measure = 90.91%. The SUS usability evaluation on the exhibition recommender feature in the virtual tour application of SMBII museum shows average score of 85.83. The machine learning-based recommender feature usability is acceptable, making it easy and attractive for visitors to find an exhibition that might match their interests.**

***Keywords—Machine learning; recommender system; museum exhibition; virtual tour; pandemic***

## I. Introduction

As institutions with educational and tourism purposes, museums must maintain their existence during the pandemic that impacts museum visits. The museum must transform into a modern museum based on digital technology to maintain its roles in pandemic situations. Utilizing the internet of things technology will benefit museums. Visitors can interact with museum collections without having physical contact with the collections, including through applications based on Augmented or virtual reality, robotics, and games [1]. Visitors can explore the museum through a virtual museum application [2]. With this application, visitors can explore every corner of the museum and the collections displayed as if they were exploring the real physical museum [3].

The problem arises when exploring the museum through a virtual tour without a guide. Visitors will be confused and need extra time to explore each exhibition room with many collections. As a result, it can lead to boredom due to the lack of clarity in the exhibition that attracts visitors and spends more time visiting [4]. Visitors will immediately leave the boring virtual space to look for other exciting spaces for educational and tourism purposes [5], especially during the pandemic where physical activity is limited. It needs a method that intelligently understands visitors' interest in the museum's exhibition and presents exciting and interactive information that satisfies visitors to explore the virtual museum.

Machine learning has been proven its effectiveness in understanding user profile and providing recommendations [6]. Based on the user profile, this algorithm learns the information extracted from past data to provide prediction of tourist destinations [7] and recommendations [8] or museum experience improvement [9]. Machine learning does not require formulating a mathematical model to predict or provide recommendations to users. The model is built based on the collected data for training the model [10]. Good training data will produce good recommendations as expected.

This study evaluates several machine learning classifier models to provide exhibition recommendations that match the user profile of a virtual museum. The boredom because of too long browsing the virtual museum displaying collections that do not match the user's interests will make the user exit the virtual tour application. Machine learning is expected to predict and recommend exciting exhibitions and match user requirements or profiles, reducing browsing time or finding interesting collections for virtual museum visitors [11]. Visitors can quickly enjoy exciting presentations and interact virtually with the collection through a virtual tour application based on machine learning recommendations, reducing boredom due to monotonous information presentations [12]. Visitors' interest will be indicated in the performance of the museum's educational and tourism roles. Visitors' knowledge about museums is expected to increase, and visitors' interest in museums through the information presented virtually [13]. The visitor will visit the physical museum when possible during a pandemic after being interested in virtual exploration and might have an economic impact on physical museums to improve the museum visit.

## II. Literature Review

Traditional museums have been transformed into modern museums based on digital technology and have begun to

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develop based on artificial intelligence and Internet of Things technology. During the pandemic, digital museums enabled museums to play their role in tourism and education by conducting virtual museum exhibitions. Like a tour guide, the exhibition recommender feature in the virtual tour application makes more accessible exploration when visitors are unfamiliar with the museum.

### *A. Use of Museum's Exhibition Virtual Tour Application*

The museum's exhibition display museum's collections that attract visitors. The visitors' experience and satisfaction depend highly on the exhibition environment [14]. Visitors can visit for a long in the museum space or even experience boredom and immediately leave negative sentiments. It impacts return visits to the museum or will affect the interest of new visitors to visit the museum.

Modern museums are transformed based on digital technology to survive in the digital era and meet the millennial's needs for speed of access to information based on internet technology with an exciting and interactive presentation [15]. The museum, identical to ancient and boring collections, presents a monotonous exhibition system, so it needs a touch of digital technology for educational and tourism purposes. The current pandemic hinders visits to physical museums and geographical constraints, such as in Indonesia, where museums with historical and cultural collections are spread across the archipelago, became barriers for visitors. Internet-based technology enables to remove the barriers. Computer technology that can present museum collections and exhibits and allow visitors to explore the museum as if they were in the real environment of a physical museum is a 360-degree virtual tour application. This technology allows visitors to interact with the museum, that presents an image of the real museum environment and interacts with 360-degree views [16]. Visitors can explore independently without the limitations of distance, space and time like a physical museum.

Some museums have integrated virtual tour applications into their virtual museums. However, it will not be easy to explore each static museum exhibition without a guide who plays a vital tourism role [17]. Suppose in a physical museum there is a guide who can suggest and direct visitors to collections or exhibitions that might interest visitors. In that case, a virtual museum should also be equipped with a virtual guide feature to reduce boredom while exploring the museum through a virtual tour application. Some museums in Indonesia [18] have integrated the virtual tour 360-degree feature in their virtual museums (Table I). However, none integrates a feature as a recommender that gives suggestions like a tour guide. The virtual museum was designed as an information system without interactive features for visitors' experience enhancement and engagement. The virtual tour feature adds value to attract physical museums because visitors will still come to physical museums to interact and experience the real museum environment, which is not obtained through virtual museums [19]. Virtual tours will engage visitors to the physical museum for tourism or educational purposes. More features need to be developed and integrated into the virtual museum for the museum's role optimization.

TABLE I. REVIEW OF INDONESIAN VIRTUAL MUSEUMS

| **Museum Object** | **Virtual Museum** | **Virtual Tour** | **RF*** |
|---|---|---|---|
| Museum Nasional | https://www.museumnasional.or.id | ✓ | x |
| Museum Bank Mandiri | https://museummandiri.wixsite.com/mbmcorner | x | x |
| Museum Tsunami | https://museumtsunami.id/ | x | x |
| Museum Balai Kirti | https://balaikirti.kemdikbud.go.id/ | ✓ | x |
| Museum Sumpah Pemuda | http://museumsumpahpemuda.kemdikbud.go.id/ | ✓ | x |
| Museum Perumusan Naskah Proklamasi | https://kebudayaan.kemdikbud.go.id/mpnp/ | x | x |
| Galeri Nasional | http://galeri-nasional.or.id/ | x | x |
| Museum Basoeki Abdullah | https://museumbasoekiabdullah.id/virtual/ | x | x |
| Benteng Vredeburg | https://vredeburg.id | x | x |
| Museum Tekstil Jakarta | https://www.mitramuseumjakarta.org/tekstil | x | x |

*RF = Recommender Feature

### *B. Machine Learning for Recommender System*

Machine learning methods have been applied to various fields such as education, economics, tourism, and cultural heritage. Machine learning models that have proven their effectiveness in the cultural field, especially museums, include K-Nearest Neighbor (KNN), Decision Tree, Random Forest, Neural Network, and Support Vector Machine [11]. Machine learning analyzes user profiles for various application purposes to improve performance, including education [20], economics and industry [21], and socio-culture [11]. An application of machine learning for museums is a recommender system. It is software providing suggestions related to decision making [22]. A recommender system is built to attract tourist visits for the tourism sector. It enables visitors to find what they need in a large museum [23]. Machine learning is applied by analyzing tourist profiles to find destinations that match the profile based on historical data. This method is effective for tourists to find travel destinations easier, especially for unfamiliar tourists with the destinations, products, or tourism services provided. ML classifier used for filtering and recommending a cultural item to explore, such as museums [23], was implemented in a mobile app but did not discuss the ML classifier selection phase. ML was also proven to give suggestions for museum curators regarding the preventive actions to be taken for historical buildings conservation [24]. However, it has no deep discussion on data processing and ML performance analysis. The app has not been built yet for user feedback evaluation, especially for the pandemic situation when users have limited access to the physical, cultural heritage such as the museum, and the climate changes during the pandemic might affect the building.

The museum is one of the exciting spaces for tourism and learning. The museum collections can be thousands, such as in the Sultan Mahmud Badaruddin II (SMBII) Palembang museum, making it is not easy for visitors to find collections that interest them. Monotonous exhibition rooms, ancient and many collections can make visitors feel bored and not excited exploring the museum virtually by just staring at the screen. The role of the tour guide is needed to provide suggestions for visits to the exhibition rooms that meet the interests of visitors so they continue to explore the museum. They are expected to provide positive sentiment for repeat visits or influence other people to visit the museum. A recommender system can act as a tour guide in the virtual museum. It gives guidance to collections or exhibitions that might interest visitors. The recommender system has been proven effective in improving students' learning achievement [25], [26]. Moreover, the recommender system is expected to enhance visitors' experience in culture education and tourism at the museum.

## III. Research Methodology

This research methodology is divided into two stages. The first is evaluating the machine learning model performance, consisting of data preparation, data processing, and performance analysis. The second stage is developing a virtual tour application implementing a machine learning model based on the performance analysis results in the first stage of this research. Fig. 1 illustrates the research methodology.

### A. Data Preparation

The dataset was developed based on measurement of the research variables related to visitor's profile. Research variables consist of independent variables and a dependent variable. The museum exhibitions interest dependent variable was influenced by 6 (six) independent variables: age, gender, origin, education, occupation, and motivation [27]. This study uses data of visitors' visits to the SMBII museum in Palembang, South Sumatra, during the COVID-19 pandemic. SMBII museum visitors remarkable decrease up to 90% during the pandemic and impact on collected data. This study assumes that museum visitors are only Indonesian citizens. Several methods are used for data preparation. Data collection was conducted using a questionnaire at the SMBII museum.

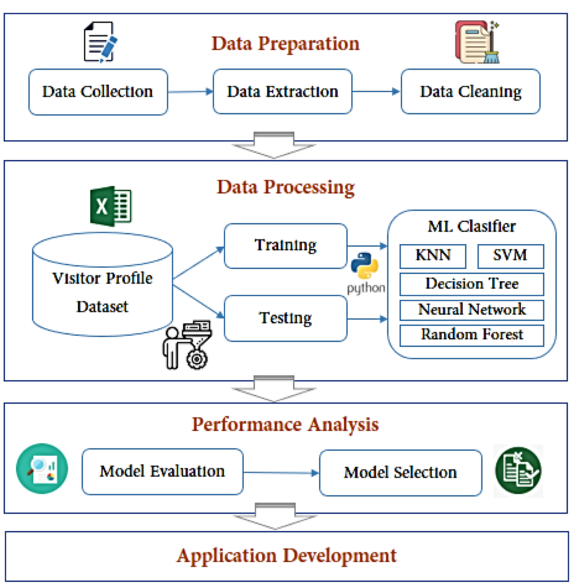
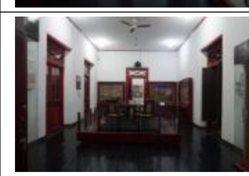
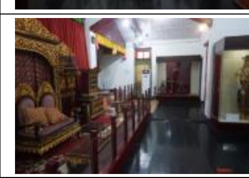



Fig. 1. Research Methodology.

*1) Instrument:* Data were collected utilizing a questionnaire containing several questions related to the visitor's profile. The questionnaire was divided into two parts. The first part contains questions related to the identity of the respondent and the second part relates to the respondent's interest in visiting the SMBII museum. After exploring the physical museum, respondents were asked to choose their favourite or most interesting exhibition room in the SMBII museum. Table II describes exhibition rooms at the SMBII museum.

TABLE II. Exhibition Rooms in SMBII Museum

| **Exhibition** | **Room View** |
|---|---|
| *Srivijaya Kingdom:* Display artefacts from the Srivijaya Kingdom, the largest kingdom in Asia |  |
| *Pre-Palembang Sultanate:* Display collection on Pre-Palembang Sultanate, a transition era after the Srivijaya Kingdom |  |
| *Palembang Sultanate:* Display artefacts collection related to Palembang Sultanate, such as SMBII painting and suit |  |
| *Colonial:* Display artefacts related to colonial era such as weapon |  |
| *Life Cycle:* Display collection of life equipment used by Palembang society in the past |  |
| *Art:* Display collection related to arts and cultures that exist since the Srivijaya Kingdom |  |
| *Craft:* Display artefacts of traditional craft such as Songket and the tool to produce it |  |

*2) Respondent:* Respondents are visitors who visited the SMBII museum during the COVID-19 pandemic. This study uses n = 550 samples with various respondents' profile to build the dataset of museum visitors during the COVID-19 pandemic. Table III describes the demographics of the respondents to develop this research dataset. After the data collection, the next step is data extraction by performing the tabulation and coding process of the data to be processed quantitatively with the machine learning (ML) model that will be tested in this study. To optimize the results of the ML classification, then the data cleaning was conducted. The possibility of incomplete data, duplication and various noises interfering with the classification process is carried out on the extracted data. The clean data is saved in .csv format with the Excel tool and ready for data processing.

TABLE III. RESPONDENT'S DEMOGRAPHY

| Factor | Critera | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 200 | 36% |
| | Female | 350 | 64% |
| Age | <22 | 330 | 60% |
| | 22-30 | 151 | 27% |
| | >30 | 69 | 13% |
| Education | High School | 276 | 50% |
| | Undergraduate | 254 | 46% |
| | Post Graduate | 20 | 4% |
| Origin | Palembang | 414 | 75% |
| | South Sumatra | 46 | 9% |
| | Sumatra | 34 | 6% |
| | Others | 56 | 10% |
| Occupation | Student | 415 | 76% |
| | Teacher/ Lecturer | 83 | 15% |
| | Employee | 41 | 7% |
| | Others | 11 | 2% |

## B. Data Processing

The dataset will be processed using some machine learning classifier models to analyze the profile of SMBII museum visitors who visit the museum in the COVID-19 pandemic situation and provide recommendations for exhibitions room that might match the visitor's interests. The dataset is divided into 80% training and 20% testing dataset. The process began with training machine learning classifier models using the training dataset. The classifier is used to classify the visitor's exhibition interest. The classifiers are Decision Tree, SVM, NN, Random forest, and KNN. The testing dataset tests the ML classifier in classifying visitor profiles and predicting interest in visiting museum exhibitions. Furthermore, the performance of the machine learning classifier model is analyzed and evaluated based on indicators of classification effectiveness accuracy, including cross-validation (CV) accuracy and F-Measure [20], [26]. A confusion matrix is also used to visualize the classification performance of ML classifier. Fig. 2 presents the confusion matrix used for the SMBII exhibition rooms interests classification, where P, Q, R, S, T, U, V represent the exhibition rooms in SMBII museum. The machine learning classifier performance indicators for exhibition classification are formulated based on the confusion matrix. Accuracy and the F-Measure formula are shown in equations (1) and (2). Based on the evaluation results of the classification effectiveness indicators obtained, selecting the best machine learning model is carried out. The selection result will be implemented for exhibition recommendation in the SMBII museum's virtual tour application. The recommendation feature is integrated into the virtual tour application and acts as a tour guide to the user who visits the virtual museum. The effective recommendation will shorten the user's time exploring museum exhibitions minimize the boredom of staring at the screen browsing for collections in museum's exhibitions.

| True Label | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| A | AA | AB | AC | AD | AE | AF | AG |
| B | BA | BB | BC | BD | BE | BF | BG |
| C | CA | CB | CC | CD | CE | CF | CG |
| D | DA | DB | DC | DD | DE | DF | DG |
| E | EA | EB | EC | ED | EE | EF | EG |
| F | FA | FB | FC | FD | FE | FF | FG |
| G | GA | GB | GC | GD | GE | GF | GG |

Predicted Label

Fig. 2. Confusion Matrix for SMBII Museum Exhibition Rooms Classification.

$$Accuracy = \frac{(AA+BB+CC+DD+EE+FF+GG)}{Number\ of\ Samples} \quad (1)$$

$$F-Measure = 2\ x\ \frac{Precision\ x\ Recall}{Precision+\ Recall} \quad (2)$$

where Precision and Recall are measured by using formula (3) and (4),

$$Precision = \frac{1}{7}\left(\frac{AA}{AA+BA+CA+DA+EA+FA+GA} + \frac{BB}{AB+BB+CB+DB+EB+FB+GB} + \frac{CC}{AC+BC+CC+DC+EC+FC+GC} + \frac{DD}{AD+BD+CD+DD+ED+FD+GD} + \frac{EE}{AE+BE+CE+DE+EE+FE+GE} + \frac{FF}{AF+BF+CF+DF+EF+FF+GF} + \frac{GG}{AG+BG+CG+DG+EG+FG+GG}\right) \quad (3)$$

$$Recall = \frac{1}{7}\left(\frac{AA}{AA+AB+AC+AD+AE+AF+AG} + \frac{BB}{BA+BB+BC+BD+BE+BF+BG} + \frac{CC}{CA+CB+CC+CD+CE+CF+CG} + \frac{DD}{DA+DB+DC+DD+DE+DF+DG} + \frac{EE}{EA+EB+EC+ED+EE+EF+EG} + \frac{FF}{FA+FB+FC+FD+FE+FF+FG} + \frac{GG}{GA+GB+GC+GD+GE+GF+GG}\right) \quad (4)$$

## C. Museum's Virtual Tour Application Development

The SMBII museum virtual tour application was developed in this study. The application development applied the Multimedia Development Life Cycle (MDLC) methodology, which consists of 6 stages (Fig. 3) [28],


Fig. 3. MDLC Methodology.

*1) Concept:* The SMBII museum's virtual tour application concept is formulated at this stage by concerning the implementation of n a machine learning model selected based on machine learning model performance analysis results of visitor profiles for museum exhibition recommendations.

*2) Design:* The design is conducted in line with the formulated concept of the SMBII museum virtual tour application. The design of the interface specifications and the functionality of the application using UML modelling is carried out at this stage. Fig. 4 shows the design of the virtual tour application's use case model diagram. The design is also carried out on the virtual tour asset content in videos, images, text, audio that will be part of the use case: Gallery, Museum History, and Virtual Tour.

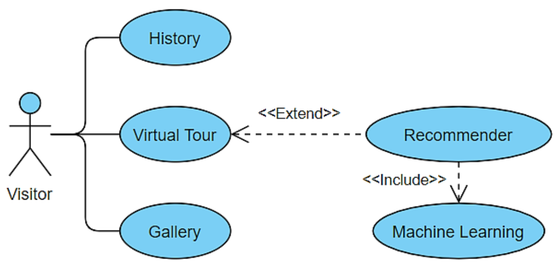



Fig. 4. Use Case Diagram of SMBII Museum's Virtual Tour App.

The Gallery use case will display information on SMBII museum collections and events. The History use case delivers the historical background of the SMBII museum as a cultural heritage protected by the Indonesian government, and the Virtual Tour use case allows users to explore the museum virtually from 360-degrees views. The Recommender use case is extended in the virtual tour use case. This use case includes machine learning to classify the exhibition room that interests visitors as a basis for recommendations given to visitors to quickly find the exhibition room that might match their interests to explore.

*3) Material collecting:* Multimedia has been designed and constructed utilizing various appropriate tools then collected for integration in the SMBII museum's virtual tour application environment. Table IV describes specific tools that must be prepared for data acquisition of asset content of the virtual tour app.

*4) Assembly:* The assembly is carried out on each virtual tour's asset in various file formats collected in the previous stage into a virtual tour application that users can run and access. The virtual tour app in this study is designed to be web-based, which makes users can use a browser to run a virtual tour of the SMBII museum without doing the application installation process.

*5) Testing:* Testing is carried out on the SMBII museum's virtual tour application to ensure each feature successfully carried out its functions as expected, including the machine learning-based exhibition recommender feature. The System Usability Scale (SUS) test was carried out to measure the level of usability of the recommender feature applied to the SMBII museum's virtual tour application by taking $n = 15$ respondents. The samples $n$ were proven effective in generalizing the test results. The samples $n$ were proven effective in generalizing the test results [29]. Fig. 5 presents the rating of usability based on the SUS score.

*6) Distribution:* After passing the testing stage, the application is uploaded to the server so that the public can widely use it via the internet to explore Palembang's cultural heritage virtually through the SMBII museum's virtual tour application, which provides machine learning-based exhibition recommendations. This recommender feature provides an alternative tour guide for visitors to explore the exhibition room that matches the interest of the SBMII museum's visitors.

TABLE IV. MATERIAL COLLECTING TOOLS

| Asset | Data Format | Acquisition Tool |
|---|---|---|
| Audio | .mp3 | Recorder |
| Video | .mp4 | Video Recorder |
| Narrative Text | .txt | Text Processor |
| Image | .jpg | Camera 360 |

| SUS Scoring | | |
|---|---|---|
| 0-64 | 65-84 | 85-100 |
| Not Acceptable | Acceptable | Excellent |

Fig. 5. Rating of SUS Score.

## IV. RESULT AND DISCUSSION

The final output of this research methodology is the SMBII museum's virtual tour application that effectively applies a machine learning model for museum exhibition recommendations. The selection of the ML model was based on the evaluation results of several ML classifier models' performance that were tested using the SMBII museum's visitor profile dataset built in this study.

### A. Dataset

The dataset contains 550 SMBII museum visitor's records consisting of data fields: age, gender, origin, education, occupation, motivation, and exhibition, representing research variables. Each variable can be related that affects the other. This study designed the exhibition variable as the dependent variable and the other six variables as independent variables. A heatmap diagram in Fig. 6 illustrates the correlation value between variables in the data set. The correlation score ($r$) is in the range of $-1< r <1$, which indicates the strength of the relation between the two variables. The closer the $r$ score is to 1, the stronger the relationship with a positive or negative impact [10].

In this study, the positive and negative signs are ignored for the numbers from the data do not indicate the numeric level but rather the label of the data coding results in the data extraction process for a quantitative approach to data processing. From the illustration in Fig. 6, it is known that the variables that have a high impact on visitors' interest in the exhibition space are gender, origin, and occupation variables, with the strongest correlation being the education variable where $r = 0.16$. The educational background of visitors gives the most substantial impact in determining the interest in the exhibition room, which is also influenced by the motivation variable where $r$ = 0.14. The visitor's education is high school and undergraduate in average came to visit a museum with the motivation of educational purposes for study or doing assignments, which is 74% (Fig. 7) with interest in the Srivijaya Kingdom exhibition room as much as 24% and the Palembang Sultanate exhibition room 34% of visits (Fig. 8). The two exhibition rooms present a collection of culture and history regarding the city of Palembang as the oldest city in Indonesia.

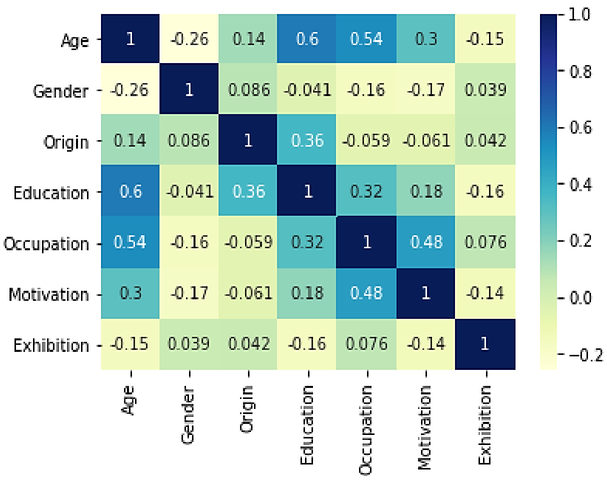



Fig. 6. Data Correlation Heatmap.

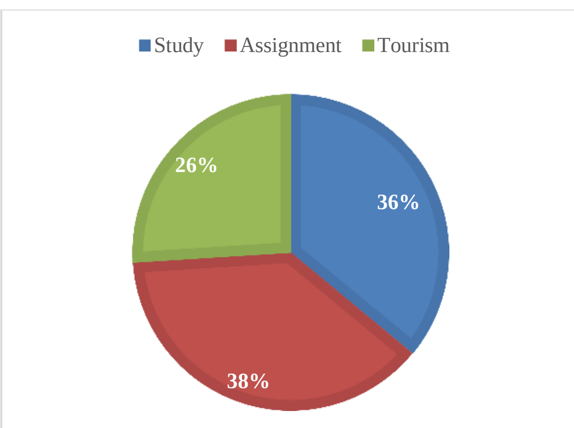



Fig. 7. SMBII Museum Visitors' Motivations.

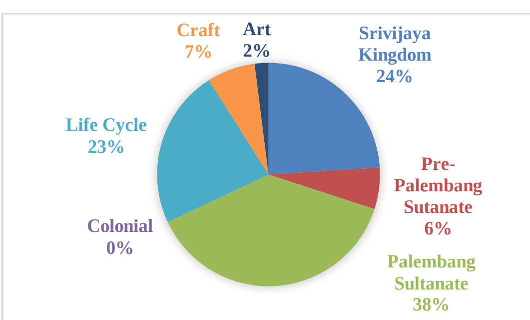



Fig. 8. Visitors' Exhibition Rooms Interests in SMBII Museum.

## B. Machine Learning Evaluation for Exhibition Recommendation

Evaluation of the machine learning model for the classification of visitors' interest exploring exhibition rooms in the SMBII museum is used to select the best model applied to the exhibition recommender feature for museum visitors through the virtual tour application developed in this study. Evaluation is carried out on the value of cross-validation accuracy and F-Measure of each machine learning model as an indicator of model performance using a dataset divided into training and testing data. Table V presents the evaluation results based on the cross-validation accuracy and F-measure indicators. Fig. 9 illustrates a graphical comparison of the performance levels of the ML classifier model evaluated in this study. Based on these results, it is known that the best model for classifying exhibition room interest in the SMBII museum based on visitor profiles is KNN with CV accuracy = 89.09% and F-Measure = 90.91%. The RF method also has high accuracy with a difference of 0.18% but a lower F-measure of 0.91%. F-measure scores were obtained based on precision and recall values using different testing data.

Cross-validation accuracy uses data that allows the same training at testing. Therefore, F-measure can show the level of accuracy when the model is used to predict or provide exhibition recommendations that match the interests of visitors to the SMBII museum. The confusion matrix shows the prediction accuracy by calculating the results of true and false predictions. It is illustrated in Fig. 10. It shows a hundred samples of testing data were true predictions. Ten samples were false predictions where the labeled-3 is the most correctly predicted, namely the Palembang Sultanate exhibition room, the favorite exhibition for visits in SMBII museum. The final selection stage determines the KNN model with the best performance for the exhibition recommender feature included in the SMBII museum's virtual tour application.

TABLE V. MACHINE LEARNING MODELS PERFORMANCE FOR CLASSIFICATION OF VISITORS' EXHIBITION ROOM INTERESTS

| Classifier | Accuracy | F-Measure |
|---|---|---|
| KNN | 89,09% | 90,91% |
| DT | 86.55% | 90,00% |
| NN | 77.64% | 73.64% |
| SVM | 53.09% | 53.64% |
| RF | 89.27% | 90.00% |

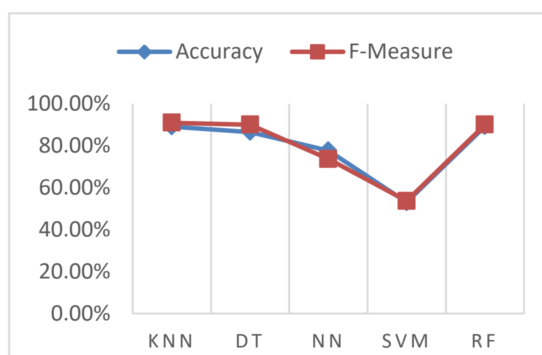



Fig. 9. Machine Learning Models Performance Comparison Visualization.

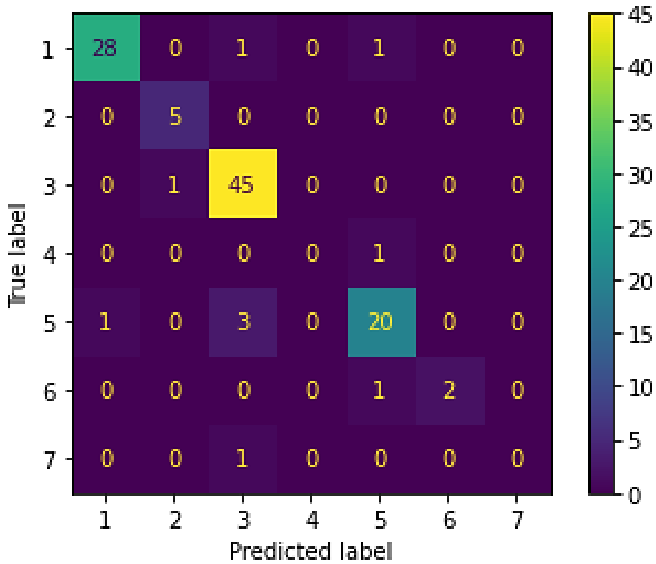



Fig. 10. Confusion Matrix of Data Testing Results.

### C. Exhibition Recommendation in Virtual Tour Application

The SMBII museum's virtual tour application was constructed utilizing 3D Vista software. The app enables users to explore the virtual museum like the physical museum with 360-degree views. Fig. 11 is the home page design of the SMBII museum's virtual tour app, which is run on a browser,

There is a tour recommender feature for visitors unfamiliar with the SMBII museum exhibition rooms on the home page. It is Pemandu Pintar (or Smart Guide) feature menu. This feature aims to help visitors find exhibition rooms and collections that are expected to match the interests of users as museum visitors who come with various demographic and motivational backgrounds, including studying, doing assignments, or tourism. Fig. 12 illustrates the interface design of an exhibition recommender feature that applies machine learning to suggest an exhibition room that might match user profiles. The user can input their profile, and then the app processes it by performing the KNN classifier. The machine learning result is presented to the user as a recommendation for starting exhibition room touring from the most interest for visitors predicted by machine learning model (Fig. 12). Users may decide to follow the given exhibition recommendation or explore the museum from the virtual museum entrance. By following the exhibition recommendation given by the machine learning classifier, users will be directed to the recommended exhibition room and then independently explore each corner of the room in 360-degrees views (Fig. 13).

An evaluation was conducted on the usability of the machine learning-based SMBII museum exhibition recommender feature in a virtual tour application. The respondents for SUS testing in this study consider variables with a strong correlation score, $r > 0.1$, on exhibition where there are independent variables: age, education, and motivation. Therefore, some samples are taken in portions based on the variable's value with the highest $r$ score, namely the education variable, while the other variables are taken randomly. The number of samples $n$ =15, the minimum size of samples is obtained for SUS testing and contains all education variable values. Table VI represents the SUS scoring results. Based on these results, it is known that the average SUS score for the exhibition recommender feature is 85.83, which can be categorized as excellent acceptable [30]. This score shows that the exhibition recommender feature implementing the best machine learning model for museum visitor profile analysis, KNN, has a good usability value to meet user needs for exhibition recommendation through SMBII museum's virtual museum application.

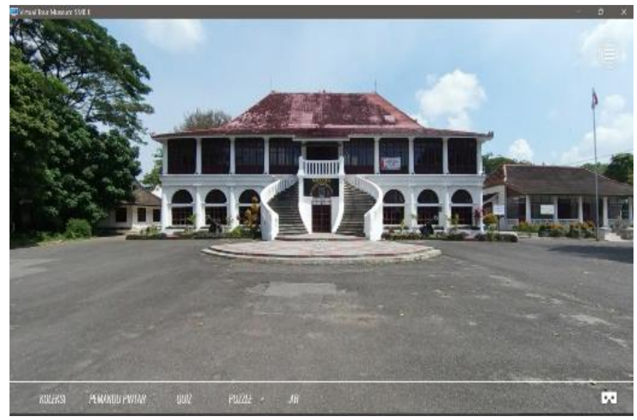


Fig. 11. User Interface of SMBII Museum’s Virtual Tour Home Page.


Fig. 12. User Interface of SMBII Museum’s Virtual Tour Recommender Feature.

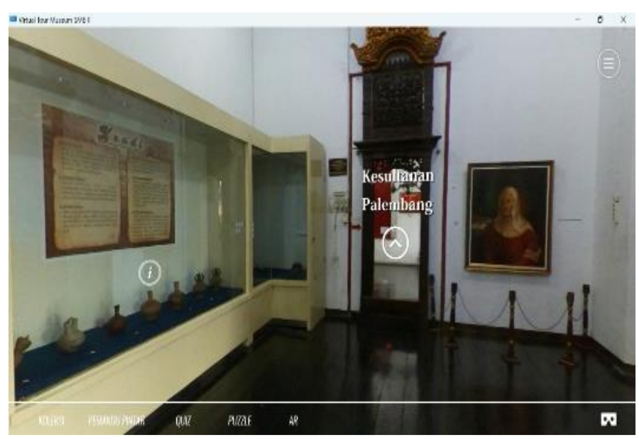



Fig. 13. User Interface of Palembang Sultanate Exhibition Room Virtual Tour.

TABLE VI. SUS SCORING RESULTS

| Respondent ID | Education | Age (years) | Motivation | SUS Score |
|---|---|---|---|---|
| 1 | High School | 13 | Assignment | 95 |
| 2 | High School | 13 | Assignment | 95 |
| 3 | High School | 14 | Assignment | 67.5 |
| 4 | High School | 14 | Assignment | 67.5 |
| 5 | High School | 14 | Assignment | 95 |
| 6 | High School | 19 | Study | 95 |
| 7 | High School | 19 | Study | 100 |
| 8 | High School | 20 | Study | 87.5 |
| 9 | Under Grad | 25 | Study | 72.5 |
| 10 | Under Grad | 27 | Tourism | 67.5 |
| 11 | Under Grad | 28 | Tourism | 80 |
| 12 | Under Grad | 33 | Tourism | 70 |
| 13 | Under Grad | 37 | Tourism | 100 |
| 14 | Post Grad | 39 | Study | 95 |
| 15 | Post Grad | 41 | Tourism | 90 |

### D. *Limitations and Contributions*

The developed SMBII museum virtual tour is assumed to be only intended for visitors to Indonesian citizens, so the dataset used has limitations, namely on regional origin and occupation factors. The profiles of the respondents of the developed dataset are dominated by museum visitors from Palembang city who were students. The situation of the COVID-19 pandemic is a reason for the small number of visits to the SMBII museum, so not much data has been collected for variations of visitor profiles. The dataset will affect ML's ability to predict visitor interest in the museum exhibition room. The more varied the data used for training, the better ML's ability in testing, especially for SMBII museum exhibition recommendation. It is necessary to add a variety of datasets to improve ML performance for predictions and recommendations of museum exhibition in the SMBII virtual museum tour application. In addition, it needs to test the ML classifier model for different datasets. The SMBII Museum is a cultural heritage that stores various collections of cultural objects. It is necessary to test whether the KNN method is still the best to recommend a visit to an exhibition if the museum presents collections other than cultural objects, such as history, art, and others.

Hopefully, a recommendation that matches visitors' interests in the museum's exhibition can provide convenience in exploring and enjoying the presentation of the museum's collections for learning and tourism purposes while reducing boredom in exploring the monotonous virtual exhibition room and making it less attractive to visitors. Visitors can quickly find the exhibition offerings that match their interests. The findings of this study can be a baseline for determining an effective ML method to be applied in an intelligent virtual tour application of a museum as a strategy to increase museum visits and enable educational and tourism roles in the COVID-19 pandemic. The recommendation feature that implements ML has proven effective in making it easier for visitors and is expected to reduce boredom in exploring the virtual museum.

## V. CONCLUSION

This study evaluates the machine learning model for exhibition recommendations given to visitors through virtual tour applications based on user or visitor profiles. The machine learning-based recommender feature in the virtual tour application will act as a tour guide that gives suggestions to the exhibition room, which might interest the museum's visitors. The best machine learning model was selected based on its performance assessed based on the cross-validation accuracy and F-measure scores. The dataset of visitor profiles consists of the exhibition variable as the dependent variable, and the independent variables are age, gender, origin, education, occupation, and motivation. The results of the correlation analysis show that the motivational variable has the strongest correlation to exhibition interest with a score of $r$ = 0.16. The dataset is then processed using the machine learning model to classify the exhibition room interest based on the profile of visitors to the SMBII museum, namely the KNN, DT, NN, SVM, and RF models. Based on testing results, it is known that the best machine learning model for classifying interest in visiting the SMBII museum's exhibition room is the KNN model with cross-validation accuracy= 89.09% and F-Measure = 90.91%. These results indicate that the machine learning model effectively predicts the interest in the SMBII museum's exhibitions room and can be applied to provide recommendations for virtual museum visitors.

The SMBII museum's virtual tour application applied the KNN method for the recommender feature of the museum's exhibition was developed using MDLC methodology. For usability evaluation, SUS testing was conducted to evaluate the usefulness of the exhibition recommendation features in the application. The testing results obtained the average SUS score = 85.83, which indicates that the recommender feature in the virtual tour application is acceptable for the user. This feature makes users easily find exhibition rooms that match their interests and explore interactive museum spaces, reducing boredom in exploring museum exhibitions with lots of rooms and thousands of historical and ancient collections, especially for millennial students. Based on the SUS scores can also be concluded that the machine learning based exhibition recommendation is easy to be used and is expected to attract public interest in visiting museums that increase museum visits for educational or tourism purposes, especially during the COVID-19 pandemic.

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