

Customer Profiling System with Residual Network-Based Face Recognition

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ABSTRACT

Customer profiling is an essential aspect of customer relationship management. Knowing who your customers are, what they need, and how to reach them is crucial in creating an effective marketing strategy. However, it can be challenging for some sellers to identify and track their loyal customers. This is where a customer profiling system can be invaluable. Such a system uses data analysis and deep learning techniques to track customer behaviour and identify preferences. One approach to customer profiling is through face recognition technology. Facial recognition is an effective method for identifying people, and it can be used to track customer attendance and identify regular customers. Therefore, this work presented the development of a customer profiling system using a deep learning technique to detect customer faces in real time. Experimental results showed that the system obtained 90% accuracy in detecting customers' faces. This work conducted a user acceptance test (UAT) to evaluate the system's effectiveness. The results indicated that the system provides many benefits and advantages to customers and sellers, including improved customer loyalty and satisfaction.

Keywords: Customer Profiling, Deep Learning, Face Recognition, Residual Network

1 INTRODUCTION

Sellers often face challenges related to managing customer visits to their premises. For example, customers are required to record their attendance each time they enter the premises, but it can be difficult for sellers to keep track of this information manually. This can lead to inefficiencies in the customer service process and waste time. Additionally, some customers prefer to buy from the same sellers and establish a loyal relationship with them. However, this can create difficulty for sellers in identifying and recognizing their loyal customers.

Customer profiling combines personal and transactional data [1] to identify purchase trends and recognize transaction information databases [2]. This information typically includes a customer's name, age, identity card, gender, address, education level, and profession [3]. In electronic commerce (e-commerce) and electronic business, customer profiling can help understand customer needs and provide ideas about the required products and services. Popular e-commerce marketplace platforms

include Lazada, Shopee, Mudah.my, Carousell, eBay, and others. Customer profiling has many benefits, including targeting the right customers, increasing response rates, attracting new customers, increasing market penetration, building customer loyalty, and facilitating account-based marketing [4]. Customer profiling enables businesses to interact with the right people at the right time, increasing marketing and sales effectiveness [5].

Face recognition (FR) technology is a widely explored field in biometrics, used to identify individuals through facial features. Compared to other biometrics such as iris, fingerprints, and palm prints [6], FR technology has gained popularity in recent years due to its potential for various applications across industries such as security and law enforcement, healthcare, education, and entertainment [7]. Organizations use FR technology in security cameras, access controls, credit card verification, and criminal identification, among other applications, to identify or authenticate a person's identity in images or real-time. FR technology uses deep learning (DL) methods, such as convolutional neural networks (CNNs), to detect and match facial features accurately stored in a database.

DL is a type of machine learning that uses artificial neural networks (ANNs) inspired by the structure and function of the brain [8]. DL models are trained using many labeled data and a multi-layer neural network architecture [9]. CNN, a type of DL model, has achieved significant success in FR due to its ability to recognize major features without human supervision [10]. CNN extracts all image characteristics, making it useful in various applications such as FR, optical character recognition, and surveillance. Using CNNs in training leads to better performance and robustness [11]. Thus, this work proposed a customer profiling system using a DL-based FR to detect and record customer attendance in real time using access data from images taken during initial customer registration.

The remaining structure of the paper is as follows: Section 2 gives a brief overview of recent studies concerning the topic. Section 3 describes the materials and methods used for developing the system. Section 4 contains the results and discussion of the proposed work. Lastly, Section 5 concludes the paper.

2 RELATED WORK

This section provides some of the research work referenced to achieve the aim of this work. Ching et al. [12] developed a visitor face-tracking system for security purposes. The system captures the visitor's face when they stand in front of a webcam for at least 10 seconds. It also provides functions such as object detection activation and data retrieval. Users can print, delete, or save the visitor's photo. Satari et al. [13] proposed an FR-based authentication system to control and track entries to an organization. This system is divided into web-based and LAN-based systems. The web-based system is used for scheduling meetings ahead of time, while the LAN-based system is used when visitors have already arrived. Gayathri et al. [14] proposed a detailed customer profile that uses demographic attributes (age and gender) to understand customers visiting the outlet. This study used CNN for image processing, which works better than RNN. This study captures video data of customers using a high-resolution camera, from which facial features are extracted. The video is sent to an FR module for FR and extraction of demographic features. The classifier identifies the customer's demographic group, and the data is stored in a database for a detailed view of the customers visiting the outlet.

Prabhulkar et al. [15] developed an automated Visitor Management System to replace the previous manual process, providing better system reliability and security. This system ensures that only authorized visitors can enter an organization's premises, as unauthenticated or false guests are prohibited. Visitors can set up an appointment using the system's Android application, which stores all data in cloud storage (Firebase). This system uses FR technology to compare a visitor's face with faces in the database. If authorized, the visitor is submitted for host confirmation and given a unique identification number. This automated solution offers a more convenient and secure approach to visitor management than previous manual techniques. Priadana et al. [16] proposed a DL approach using a CNN to predict the gender of Instagram users based on their profile images. DL is a well-known method to extract hidden patterns in an image. According to the performance study results, the gender prediction on Instagram based on profile images using CNN had a 70.11% accuracy rate. This study shows that gender prediction based on image analysis using CNN can be conducted very effectively, particularly image analysis based on the image profile of Instagram users.

Strueva and Ivanova [17] studied the process, methods, and FR algorithms to develop a student attendance control system. This study proposed a method to improve recognition accuracy and implemented it in the attendance tracking system. This system comprises an image capture module, face identification module, and web application. The image-capturing module is connected to a camera in the classroom, which separates the video stream into frames, and the FR module is called for each image. During operation, the FR module connects to the faces database, which stores student passport data. The user interacts with the web application to track attendance and access data. The face identification process has three stages: face detection, feature extraction, and FR. The face detection stage determines the location of human faces in the input image, while the feature extraction stage identifies the features of the recognized people. The FR stage compares the feature descriptors generated for each face with the face descriptors stored in the faces database, resulting in identification or verification of identity. Table 1 presents a summary of previous research studies.

Briefly, previous studies have proposed computerized systems using FR technology to manage, monitor, and control customers more efficiently. These systems replaced the manual recording of customer information with fully automated processes. The systems stored customer information in a centralized database server for generating reports and analyses. Also, previous studies highlighted the potential benefits of using computerized systems with FR technology for customer management, such as improved efficiency and accuracy, automated data processing, and centralized data storage for easy access and analysis.

Therefore, this work proposed a customer profiling system that integrates residual network-based FR with Android apps to enable real-time detection and recording of customer attendance while simplifying user engagement. This allows customer profiling to obtain daily attendance data, which customers can easily access and view through a mobile application. The attendance data is then used to identify loyal customers, allowing sellers to recognize and reward them accordingly. The expected outcome of this system design is to increase the efficiency of the business process.

| Author (s) | Publication Year | Research Title | Method | Library | Accuracy (%) | |
|-----------------------------|---------------------|--|----------------|-------------------|-----------------|--|
| Ching et al. [12] | 2009 | Visitor Face Tracking System using OpenCV Library | - | OpenCV | - | |
| Satari et al. [13] | 2015 | Face Recognition for Security Efficiency in Managing and Monitoring Visitors of an Organization | - | EmguCV | - | |
| Gayathri et al. [14] | 2020 | Customer Profiling using Demographic Analysis by Video Face Detection and Recognition | CNN | - | - | |
| Prabhulkar et al. [15] | 2020 | Visitor Management System using Convolutional Neural Network | CNN | Dlib/ Firebase | - | |
| Priadana et al. [16] | 2020 | Gender Prediction for Instagram User Profiling using Deep Learning | CNN/ ResNet | OpenCV | 70.11 | |
| Strueva and Ivanova [17] | 2021 | Student Attendance Control System with Face Recognition based on Neural Network | CNN/ ResNet | OpenCV | 86.00 | |

Table 1 : Summary of previous research studies

3 MATERIAL AND METHODS

3.1 Face Recognition Architecture



Figure 1 : Application architecture

The customer profiling system has three main components, as shown in Figure 1. Firstly, the application server stores attendance records generated by the camera, which recognizes customers' faces. Secondly, the camera captures images of customers' faces and sends them to a personal computer (PC) for processing using a DL technique. The PC detects important facial features to identify customers and stores the attendance records in the application server. Finally, customers can use an Android mobile device to access their attendance records, which connects to the application server to retrieve the data. Sellers can also use the data collected from the application to tailor their marketing efforts to meet the needs and preferences of their customers, ultimately improving customer satisfaction and loyalty.

In summary, the customer profiling system uses a combination of hardware (camera and PC) and software (a DL technique and Android mobile device) to track customer attendance and identify loyal customers. The process involves capturing facial images, processing images using a DL technique, and storing attendance records on the application server for future reference. Customers can then access this data using an Android mobile device, providing a personalized experience, and enabling sellers to improve customer satisfaction and loyalty.

3.2 Development Process

3.2.1 Sitemap

This work visualized a sitemap that overviews the system's functionality. Figure 2 illustrates the login/ signup process users must complete before accessing the system menu. The menu contains five interfaces: user details, graphs, attendance, loyal customers, and about us. The user details page displays the user's profile image, username, phone number, and email address. Users can edit their phone number and profile image and then choose to accept or cancel the changes. The graphs page allows admins to view customer traffic for the past few months, helping them to plan business strategies. Admins can also view daily or monthly attendance data. The system also includes a loyal customer page where admins can edit customer loyalty variables and generate a list of loyal customers if the criteria are met. Finally, the about us page briefly describes the developer and the company's history. Overall, the system menu provides comprehensive tools for managing customer data and improving customer loyalty.



Figure 2 : Sitemap

3.2.2 Process Flowchart

Flowcharts are used to illustrate process stages graphically. Figure 3 and Figure 4 show a user flowchart and an admin flowchart.



Figure 3 : User flowchart





3.3 Convolutional Neural Network (CNN) Architecture

To build a customer profiling system, CNN is used to process input images and generate an output probability for each class [18]. The CNN architecture consists of several layers: a convolutional layer, a pooling layer, a rectified linear unit (ReLU) activation function, and a fully connected (FC) layer.

The convolutional layer extracts features from input training data [19], [20] using mathematical operations with a kernel and feature map. The pooling layer minimizes convolutional layer output size by summarizing features within image regions. The ReLU activation function introduces non-linearity in a CNN by setting negative values to zero, enabling networks to learn complex features, mitigate vanishing gradient problems, and prioritize important information during training [18]. The

FC layer performs a linear transformation on the output of the pooling layer to produce a prediction for the image class.

After extracting high-level features from images, FC-dense layers perform classification tasks. The input image is flattened and processed through FC layers with weights and biases connecting neurons. The dropout layer is used to reduce overfitting. The SoftMax activation determines the final output class based on the highest probability score, enhancing accuracy. The Adam optimizer calculates learning rates for different parameters individually [21], and cross-entropy measures the system's performance. The result of the classification component is the system's classification output. The architecture of CNN is shown in Figure 5.



Figure 5 : Basic CNN architecture [10]

3.3.1 Residual Network (ResNet) Architecture for Face Recognition

ResNet [22] is a popular DL architecture used successfully in various computer vision applications [23]. It stands for Residual Network and is designed to address the vanishing gradients issue [10], [24], [25] in very deep neural networks. This work used a simple ResNet model that balances computational efficiency and effectiveness for FR.

To perform FR, a simple ResNet model extracts features from input images. These features are then used to classify faces into a particular category. Firstly, convolutional layers extract features from input images using a series of filters. Each filter is applied to a small region of images to extract a specific feature. Then, pooling layers reduce feature map sizes produced by convolutional layers. This helps to reduce the number of parameters in the model and makes it more computationally efficient. Next, ReLU activation functions allow the model to learn more complex features from input images by enabling the model to learn non-linear relationships between input features.

The ResNet model also uses shortcut connections in residual blocks (see Figure 6). This allows the model to learn features at different scales by bypassing convolutional layers and directly connecting the input of the block to the output. This is important for FR because faces can vary in size, orientation, and lighting conditions.

The mathematical equation for the shortcut connection (1) is as follows [22]:

$$shortcut = x + f(x) \tag{1}$$

where the *shortcut* is the output of the shortcut connection. x is the input to the block, and f(x) is the output of the convolutional layers.



Figure 6 : Residual learning block [22]

The mathematical equations for the ResNet model convolutional layers are similar to those used in other CNNs. The main difference is that the ResNet model uses batch normalization after each convolutional layer. Batch normalization helps stabilize the training process and improve the model's performance.

The following is an example of a mathematical equation for the convolutional layer in the ResNet model (2) [22]:

$$y = f(x) = W \times x + b \tag{2}$$

where *y* is the output of the convolutional layer, and *x* is the input of the convolutional layer. *W* is the weight matrix, and *b* is the bias vector.

After that, the FC layer takes the output of the last convolutional layer and produces a probability distribution over different categories. The category with the highest probability is then predicted to be the identity of the face.

The mathematical aspects of the ResNet model contribute to its effectiveness for FR in several ways. First, the model can learn features at different scales due to the shortcut connections in residual blocks. Second, the model uses ReLU activation functions to learn more complex features from the input images. Third, the model uses a cross-entropy loss function, which is well-suited for classification tasks such as FR.

Overall, ResNet is a robust DL architecture for FR in customer profiling systems. It offers a good balance between accuracy, efficiency, and robustness.

3.4 Develop an Android-based Customer Profiling System using Face Recognition

3.4.1 Face Recognition System Flow Diagram



Figure 7 : FR system flow diagram

The flow diagram illustrates four FR system stages, as shown in Figure 7. The first stage involves detecting the location of all faces within the image. The second stage includes aligning and projecting faces. After alignment and projection are complete, faces are encoded to create a set of features that can be used to identify each face. The final stage involves extracting facial features from the encoded data and using them to perform FR.

3.4.2 Face Recognition System Program

This section highlights several important parts of developing a FR model, such as retrieving user data from Firebase, encoding faces, marking attendance, and detecting faces in a video stream.

a) This code retrieves user data from Firebase, downloads user images, and saves them in a folder called "image_cust" (see Figure 8).

```
# Retrieve user data from Firebase
users = db.child("users").get()
# Download user images from URLs and save them in the 'image_cust' folder
for user in users.each():
    values = user.val()
    email = values['email']
    image = values['image']
    name = values['image']
    name = values['pnum']
    fullfilename = os.path.join(folder, str(pnum + ' ' + name + '.jpg'))
    urllib.request.urlretrieve(image, fullfilename)
```

Figure 8 : Retrieve user data from Firebase codes

b) This code gets a list of all images in a folder. Then, for each image, it loads and encodes it using a pre-trained FR model. The encoded images are then stored in a list (see Figure 9).

```
# Load images from 'image_cust' folder and encode them
images = []
classNames = []
myList = os.listdir(folder)
for cl in myList:
    curImg = cv2.imread(f'{folder}/{cl}')
    images.append(curImg)
```

```
classNames.append(os.path.splitext(cl)[0])
print(classNames)
```

```
Figure 9 : Load and encode image codes
```

c) This code marks attendance for a user by checking if they have already marked attendance for the day. If not, the code saves their attendance record to a file and a database (see Figure 10).

```
with open('Attendance.csv', 'r+') as f:
   myDataList = f.readlines()
   nameList = []
    for n in range(1, 101):
        checkday = datetime.today() - timedelta(days=n)
        checkday = checkday.strftime('%d/%m/%Y')
        if checkday in todaydateList:
            yesterday = datetime.today() - timedelta(days=n)
            break
        else:
            yesterday = datetime.now()
   if now > yesterday:
        c.seek(0)
        c.truncate()
        c.writelines(f'{"Name"}, {"Date"}')
   for line in myDataList:
        entry = line.split(',')
        nameList.append(entry[0])
   if name not in todaynameList and name != 'Name':
f.writelines(f'\n{name}, {dtString}')
        c.writelines(f'\n{name}, {dtString}')
        data = {"date": dtString, "phone": name}
        db.child("attendance").push(data)
```

Figure 10 : Mark attendance codes

d) This code detects faces in a video stream and then compares the detected faces to a list of known faces. If there is a match, the code marks attendance for the person and displays their name on the screen (see Figure 11).

```
for encodeFace, faceLoc in zip(encodesCurFrame, facesCurFrame):
    matches = face_recognition.compare_faces(encodeListKnown, encodeFace)
    faceDis = face_recognition.face_distance(encodeListKnown, encodeFace)
    matchIndex = np.argmin(faceDis)

if matches[matchIndex]:
    Name = classNames[matchIndex].upper()
    name = Name.split(' ')
    split = ' '.join(Name.split()[1:])
    # print(name)
    y1, x2, y2, x1 = faceLoc
    y1, x2, y2, x1 = faceLoc
    y1, x2, y2, x1 = y1 * 4, x2 * 4, y2 * 4, x1 * 4
    cv2.rectangle(img, (x1, y1), (x2, y2), (0, 255, 0), 2)
    cv2.rectangle(img, (x1, y2 - 35), (x2, y2), (0, 255, 0), cv2.FILLED)
    cv2.putText(img, "Customer", (x1 + 6, y2 - 6),
cv2.FONT HERSHEY COMPLEX, 1, (255, 255, 255), 2)
```

cv2.putText(img, split, (10, 30), cv2.FONT_HERSHEY_COMPLEX, 1, (255,255,255), 2) markAttendance(name[0])

Figure 11 : Face recognition codes

3.4.3 Program Codes for Application

This section describes several important parts of developing an Android-based customer profiling system. The system can track customer attendance, including monthly and loyal customer attendance.

a) Monthly Attendance: Fetches all attendance data from Firebase and filters it based on the selected month (see Figure 12).

Figure 12 : Monthly attendance codes

b) Loyal Customer Attendance: Retrieves attendance data from Firebase and calculates the frequency of visits for each customer (see Figure 13).

```
root2.addValueEventListener(new ValueEventListener() {
    @Override
    public void onDataChange(@NonNull DataSnapshot snapshot) {
        List<User3> tempUsersList = new ArrayList<>();
        // Create a HashSet to track unique phone numbers
        HashSet<Long> uniquePhoneNumbers = new HashSet<>();
        for (DataSnapshot dataSnapshot : snapshot.getChildren()) {
            String sDate1 =
        dataSnapshot.child("date").getValue(String.class);
            String[] dateParts = sDate1.split("/");
            String month = dateParts[1];
            String phone1 =
        dataSnapshot.child("phone").getValue(String.class);
            Long phone = Long.parseLong(phone1);
        }
    }
}
```

Figure 13 : Loyal customer attendance codes

3.5 Hardware and Software Requirements

The specifications of the hardware and software requirements of this work are shown below:

- a) Hardware Requirements: This work used a laptop with the following setup specifications: Intel (R) Core (TM) i5-8300H CPU @ 2.30GHz, 4 GB RAM, 64-bit operating system, x64-based processor, Windows 10, and NVIDIA GeForce GTX 1050. This work used a smartphone with Android 4.1.1 and 2 GB of RAM. This work used a web camera with 1080p Full HD.
- b) Software Requirements: This work used Android Studio to develop a mobile app, Google Firebase for reporting and analytics, and PyCharm to develop a FR system using Python interpreters. Table 2 lists Python packages and their versions that need to be installed.

| Package | Version | | | |
|------------------|----------|--|--|--|
| Cmake | 3.17.2 | | | |
| Dlib | 19.18.0 | | | |
| Face recognition | 1.3.0 | | | |
| Numpy | 1.19.01 | | | |
| OpenCV | 4.2.0.34 | | | |

| Table | 2 : | Python | package |
|-------|-----|--------|---------|
|-------|-----|--------|---------|

4 RESULTS AND DISCUSSION

4.1 Experimental Results

4.1.1 Interface of Customer Profiling System with Residual Network-Based Face Recognition

The system interface design consists of login, register, dashboard, graph, attendance list, and about us pages, as displayed in Figure 14.



Figure 14 : Example of system interface design: login (a), register (b), dashboard (c), graph (d), attendance list (e), and about us (f)

4.1.2 Sample Output

The experiment used 15 user profile images extracted from attendance records in the application server to perform real-time detection to identify customers' faces. The screen displayed the "Customer" class in the face area of each picture and the customer's name above. The results indicated that the detection process successfully predicted every face in the images as belonging to a customer (see Figure 15).



Figure 15 : Sample output, (a) and (b)

The accuracy of 90% achieved by the detection method is considered reasonable compared to related research in the field (see Table 3). This high level of accuracy is likely due to the high quality of the images taken during the experiment. The high-quality images provided clear and detailed images of customers' faces, which made it easier for the detection method to identify and classify them accurately. However, further testing and analysis may be necessary to evaluate the effectiveness and reliability of the detection method fully.

| Author (s) | Method | Accuracy (%) |
|--------------------------|--------|--------------|
| Priadana et al. [16] | ResNet | 70.11 |
| Strueva and Ivanova [17] | ResNet | 86.00 |
| Proposed | ResNet | 90.00 |

Table 3 : Comparison with previous work

4.1.3 Attendance Report

The customer profiling system generated a real-time attendance report that could be viewed on Android devices or Excel spreadsheets (see Figure 16). This flexibility allowed sellers to track customer attendance on their preferred devices and identify loyal customers. The report also provided valuable insights into customer behaviour, such as which customers visited most often. The report was presented clearly and concisely, making it easy for sellers to identify trends and patterns in customer attendance. Overall, the attendance report feature of the customer profiling system was a powerful tool for managing customer relationships and optimizing business operations.

| CPS Admin | AutoSave 💽 🗗 🌱 🗸 🤜 | Attendand |
|-------------------------|--|--|
| Loyal Customer | File Home Insert Page Layout Formulas Paste $\overset{\sim}{\square}$ | Data Revie = = = ≫ - = = = = |
| Minimum of 2 GENERATE | Clipboard Ty Font Ty | |
| Attendance | A B C | D E |
| Martin Martin | 1 Name Date Phone | |
| | 2 Muhammad Asyraaf 23/10/2022 1139125019 | |
| | 3 Siddiq 23/10/2022 132024413 | |
| | 4 Muhammad Asyraaf 24/10/2022 1139125019 | |
| Name : Muhammad Asyraaf | 5 Afif Muzani 24/10/2022 146064046 | |
| Phone: 01139125019 | 6 Tuan Wafiq 24/10/2022 164952745 | |
| Frequency: 6 | 7 Athirah 24/10/2022 139461892 | |
| | 8 Athirah 24/10/2022 189145334 | |
| Name : Siddig | 9 Athirah 24/10/2022 167375145 | |
| Phone : 0132024413 | 10 Siddiq 24/10/2022 132024413 | |
| Frequency : 2 | 11 Athiran 24/10/2022 129885145 | |
| Frequency. 5 | 12 Munammad Asyraat 25/10/2022 1139125019 | |
| | 15 Sidulq 25/10/2022 152024415 | |
| Name : Afif Muzani | 15 Athirah 25/10/2022 129663145 | |
| Phone: 0146064046 | 16 Afif Muzani 25/10/2022 146064046 | |
| Frequency: 2 | 17 Athirah 25/10/2022 189145334 | |
| | 18 Tuan Wafiq 25/10/2022 164952745 | |
| Name : Tuan Wafig | 19 Athirah 25/10/2022 167375145 | |
| Phone : 0164052745 | 20 Muhammad Asyraaf 26/10/2022 1139125019 | |
| | 21 Muhammad Asyraaf 27/10/2022 1139125019 | |
| Frequency: 2 | 22 Athirah 27/10/2022 189145334 | |
| (a) | (b) | |

Figure 16 : Attendance report on Android-based devices (a) and Excel spreadsheets (b)

4.2 User Acceptance Test

User Acceptance Test (UAT), also known as beta testing, application testing, or end-user testing, is a crucial phase in application development. It involves presenting the application to its target users for testing to gather feedback and identify any faults or flaws in the system, enabling improvements and alterations in the future.

To evaluate system performance, 15 respondents, customers experienced with automotive workshops, were chosen as a sample. User evaluations were conducted using Google Forms, automatically displaying analysis results. The analysis results were described as a percentage of five options available: Strongly Disagree (1), Disagree (2), Not Sure (3), Agree (4), and Strongly Agree (5).

Table 4 presents user evaluation results for "Customer Profiling System with Residual Network-Based Face Recognition". The feedback received was overwhelmingly positive. Respondents reacted favorably to the system, indicating high satisfaction with its performance. Specifically, 60% of the respondents rated the system as "strongly agree" and the remaining 40% as "agree" regarding its usefulness. Moreover, most respondents said the system was user-friendly, making it easy to navigate and perform tasks. These positive comments can be valuable for future system improvements, highlighting areas where the system excels and where further enhancements could be made to better meet the users' needs.

| Questions | | Percentage (%) | | | | |
|-----------|--|----------------|---|---|----|----|
| | | 1 | 2 | 3 | 4 | 5 |
| 1. | This mobile application is easy to learn and use. | - | - | - | 40 | 60 |
| 2. | The user interface of this mobile application is intuitive and user-friendly. | - | - | - | 40 | 60 |
| 3. | The features and functions of this mobile application are well-organized and easy to access. | - | - | - | 40 | 60 |
| 4. | This mobile application makes obtaining attendance data easier. | - | - | - | 40 | 60 |

Table 4 : User evaluation results.

4.3 System Usefulness and System Design

Based on the collected data, most respondents claimed that the system was beneficial and could be used in the future. The system is helpful since it is user-friendly and suitable for all individuals. The system was developed in English, a global language, so the user could better understand its operation. Then, the button created was user-friendly, and its colour stood out from the background. The design is simple and minimalistic, which makes it attractive to customers. The system also has several features that make it easier and more functional. Finally, the selected colour is purple, representing loyalty, strength, elegance, and ambition. It fits the system as it was created to find loyal customers.

5 CONCLUSION

This work proposed a customer profiling system using residual network-based face recognition to detect customer faces in real time. The system tracks customer attendance and identifies loyal customers through facial features. It enables sellers to better understand their customers' preferences and tailor their marketing efforts to meet their needs, ultimately improving customer satisfaction and loyalty. Results of a UAT showed that the system is a suitable replacement for the manual method, with 90% accuracy in detecting customers' faces. However, further investigation is required to improve the system's recognition of faces when customers move or turn in different directions. Overall, this work provides a novel and effective approach to customer profiling that has the potential to enhance customer relationship management and improve customer satisfaction and loyalty. The system successfully detects and identifies customers' faces, allowing for the classification of regular and new customers.

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REFERENCES

- M. M. Hassan, "Customer Profiling and Segmentation in Retail Banks using Data Mining Techniques," *Int. J. Adv. Res. Comput. Sci.*, vol. 9, no. 4, pp. 24–29, 2018, doi: 10.26483/ijarcs.v9i4.6172.
- [2] A. Mukhlas, A. Ahmad, and Z. Zainun, "Data Mining Technique: Towards Supporting Local Cooperative Society in Customer Profiling, Market Analysis and Prototype Construction," *ICICTM* 2016 - Proc. 1st Int. Conf. Inf. Commun. Technol., pp. 109–114, 2017, doi: 10.1109/ICICTM.2016.7890786.
- [3] F. Ntawanga, "Customer Profiling using a Service-Oriented Architecture," 2010.
- [4] H. Bhasin, "Customer Profiling Definition and Benefits (with Steps Explained)." [Online]. Available: https://www.marketing91.com/customer-profiling/.
- [5] "What are Customer Profiling and its Undeniable Benefits to Business?," *Quantzig*. [Online]. Available: https://www.quantzig.com/blog/customer-profile/.
- [6] Y. Bharat Chandra and G. Karthikeya Reddy, "A Comparative Analysis of Face Recognition Models on Masked Faces," *Int. J. Sci. Technol. Res.*, vol. 9, no. 10, pp. 175–178, 2020.
- [7] O. Arora, R. Purohit, H. Samant, and A. Gulati, "Attendance System using Face Recognition," *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol.*, vol. 6, no. 2, pp. 164–171, 2020, doi: 10.32628/CSEIT206243.
- [8] J. Brownlee, "What is Deep Learning?," *Machine Learning Mastery*. [Online]. Available: https://machinelearningmastery.com/what-is-deep-learning/.
- [9] "What Is Deep Learning?," *MathWorks*. [Online]. Available: https://www.mathworks.com/discovery/deep-learning.html.
- [10] L. Alzubaidi *et al.*, *Review of Deep Learning: Concepts, CNN Architectures, Challenges, Applications, Future Directions*, vol. 8, no. 1. Springer International Publishing, 2021.
- [11] P. Munjal, V. Rattan, R. Dua, and V. Malik, "Real-Time Face Mask Detection using Deep Learning," *J. Technol. Manag. Grow. Econ.*, vol. 12, no. 1, pp. 25–31, 2021, doi: 10.15415/jtmge.2021.121003.
- [12] Y. K. Ching, A. S. Prabuwono, and R. Sulaiman, "Visitor Face Tracking System using OpenCV Library," SCOReD2009 - Proc. 2009 IEEE Student Conf. Res. Dev., pp. 196–199, 2009, doi: 10.1109/SCORED.2009.5443146.
- [13] B. S. Satari, N. A. Abd Rahman, and Z. M. Zainal Abidin, "Face Recognition for Security Efficiency in Managing and Monitoring Visitors of an Organization," *Proc. - 2014 Int. Symp. Biometrics Secur. Technol. ISBAST 2014*, pp. 95–101, 2015, doi: 10.1109/ISBAST.2014.7013101.
- [14] M. Gayathri, S. Jha, M. Parmar, and C. Malathy, "Customer Profiling using Demographic Analysis by Video Face Detection and Recognition," *Proc. 5th Int. Conf. Inven. Comput. Technol. ICICT*

2020, pp. 570–575, 2020, doi: 10.1109/ICICT48043.2020.9112397.

- [15] P. Prabhulkar, D. Adulkar, and C. Gurav, "Visitor Management System using Convolutional Neural Network," vol. 8, no. 4, pp. 211–221, 2020.
- [16] A. Priadana, M. R. Maarif, and M. Habibi, "Gender Prediction for Instagram User Profiling using Deep Learning," 2020 Int. Conf. Decis. Aid Sci. Appl. DASA 2020, pp. 432–436, 2020, doi: 10.1109/DASA51403.2020.9317143.
- [17] A. Y. Strueva and E. V. Ivanova, "Student Attendance Control System with Face Recognition based on Neural Network," 2021 Int. Russ. Autom. Conf., pp. 929–933, 2021, doi: 10.1109/RusAutoCon52004.2021.9537386.
- [18] E. Zhang, "A Real-Time Deep Transfer Learning Model for Facial Mask Detection," *2021 Integr. Commun. Navig. Surveill. Conf.*, pp. 1–7, 2021, doi: 10.1109/ICNS52807.2021.9441582.
- [19] V. S, S. A, V. G, and U. A, "Face Mask Attendance System based on Image Recognition," 2021.
- [20] S. Sudhakar, "Convolution Neural Network for Beginners," *Towards Data Science*, 2017.
 [Online]. Available: https://towardsdatascience.com/convolution-neural-networke9b864ac1e6c.
- [21] J. Raghavan and M. Ahmadi, "Preprocessing Techniques to Improve CNN based Face Recognition System," *Comput. Sci. Inf. Technol. (CS IT)*, pp. 1–20, 2021, doi: 10.5121/csit.2021.110101.
- [22] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 770–778, 2015, doi: 10.1109/CVPR.2016.90.
- [23] S. A. G. Shakhadri, "Build ResNet from Scratch With Python!," *Analytics Vidhya*, 2021. [Online]. Available: https://www.analyticsvidhya.com/blog/2021/06/build-resnet-from-scratch-with-python/.
- [24] P. Ruiz, "Understanding and Visualizing ResNets," *Medium*, 2018. [Online]. Available: https://towardsdatascience.com/understanding-and-visualizing-resnets-442284831be8.
- [25] "ResNet: The Basics and 3 ResNet Extensions," *datagen*. [Online]. Available: https://datagen.tech/guides/computer-vision/resnet/.