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Enhancing Customer Service Delivery in Insurance Companies Using Convolutional Neural Network for Face Recognition: Evidence from Rwanda

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Abstract:- Insurance companies continue to struggle to deliver effective customer service and automated client interactions in the modern digital world. This problem becomes evident when serving customers who have lost their physical documents or when fraud occurs. In response to these challenges, a face recognition system was created to enhance customer identification and mitigate fraud risks within insurance companies. The system matches customer faces with the information stored in three databases, thereby enhancing customer service and security measures. The Multi-Task Cascaded Convolutional Neural Networks (MTCNN) and VGGface models were used for face detection and recognition, while SQLite databases were employed for storing customer information. The streamlit Python package was used to input the uploaded image or camera image and the visualization of system output. The developed face recognition system offers insurance companies a means to identify customers through image recognition to improve customer service, increase their efficiency in their activities and avoid frauds that may lead to these insurance companies' bankruptcy. This system can be seamlessly integrated with existing systems and applied in multiple areas, including customer service, security, and access control. Overall, it provides a practical solution for insurance companies to improve performance and organizational culture while reducing the risk of fraud. The accuracy of the developed recognition approach is 96% which is higher when compared to other existing approaches.

Keywords:- *Convolution Neural Network, Face Recognition, Machine Learning, Feature Extraction, Deep Learning, Face Matching.*

I. INTRODUCTION

Face detection technology has been in existence for a considerable period and has found applications in various domains [1]. It has been successfully utilized in entertainment, law enforcement, and biometrics. Insurance companies face challenges in delivering exceptional customer service while ensuring operational efficiency [2]. Manual identification processes and data management can be time-consuming, error-prone, and hinder the overall customer experience. To address these challenges, emerging technologies such as face recognition offer promising solutions [3].

Insurance companies encounter difficulties in efficiently capturing and utilizing customer information, resulting in slower service delivery, potential errors, and limited personalization [4]. Traditional identification methods rely on manual verification processes, which can be labor-intensive and prone to errors. Managing large volumes of customer data and ensuring its security and accessibility pose significant challenges. Therefore, there is a need to adopt advanced technologies that can streamline customer service processes and improve overall operational efficiency.

II. LITERATURE REVIEW

Previous studies have shown the potential benefits of face recognition in industries like security, retail, and healthcare. However, limited research exists on its use in insurance for improving customer service through accurate identification, enhanced security, and personalized experiences. Researchers have explored various approaches to face recognition, leveraging techniques such as Convolutional Neural Network (CNN), hybrid systems, deep learning algorithms, and attribute prediction models. For instance, [5] proposed a long-distance face recognition method using a CNN and achieved superior performance across varying distances. [6] introduced a hybrid system combining a CNN and Logistic Regression Classifier

(LRC), which demonstrated improved accuracy and reduced processing time.

Other studies have focused on deep learning algorithms and models for face recognition. [7] proposed a nine-layer CNN-based face identification system, while [8] implemented a Deep Learning algorithm using the FaceNet neural network architecture. The researchers [9] developed an Active Face Recognition system (AcFR) using a pre-trained VGG-Face CNN, and [10] introduced a new face recognition system using a deep C2D-CNN model at the decision level.

Additionally, [11] presented a deep learning model that enhanced face identification performance by predicting facial attributes, and [12] proposed a Deep CNN with multiple inputs for robust face recognition. They surveyed different face recognition techniques and implemented a face recognition system using a Deep Neural Network.

This research introduces CNN-based face recognition in insurance to enhance customer service. It utilizes MTCNN and VGGFace models for accurate face detection and feature extraction. The system employs face-matching algorithms for efficient customer identification. Deep learning, image processing, and database management are employed. Extensive testing will evaluate real-world performance. The research contributes a practical solution to streamline customer identification, improve service efficiency, and enhance customer satisfaction in insurance companies.

The paper is structured as follows: after section one that makes a general introduction, section 2 details the methods and techniques used to develop the face recognition system. Section 3 presents the system's performance results and interpretations. Section 4 discusses the benefits of face recognition in insurance companies. Section 5 offers recommendations for integration and future research. Finally, Section 6 summarizes the main findings and their significance in enhancing customer service in insurance.

III. METHODS AND TECHNIQUES

A. Data

In our study, we collected customer face images along with their information and stored them in the database for training and recognition purposes. Each set of images collected for an individual customer is referred to as a dataset, as shown in Figure 1, which is essential for training the VGG-face model and achieving accurate recognition.

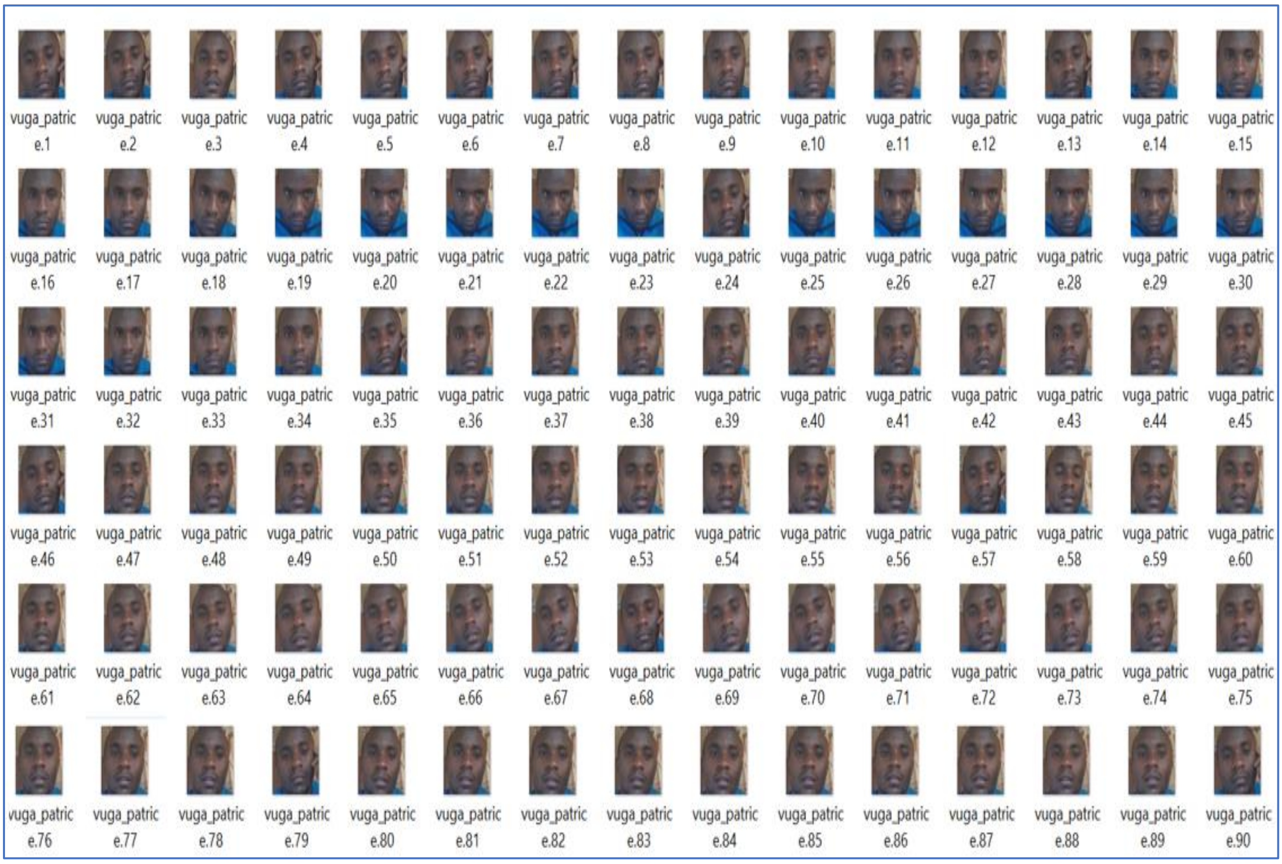

Fig. 1: Example of Customer Dataset

To create a diverse dataset, we collected 100 face images from Kaggle.com, ensuring variation in expressions, poses, and lighting. We also used a webcam to capture photos of insurance customers during registration, recording 100 face samples per user. The face detection algorithm identified and extracted faces, which were then cropped based on provided coordinates.

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Our dataset included over 10,000 images from 102 customers, training the VGG-face model. The diverse dataset allowed the model to learn well from the dataset. Updates can be made by adding more users and retraining. Images were resized to (64, 64) pixels for consistency. This comprehensive dataset was crucial in training the accurate face recognition model.

B. Methods

The face recognition system was developed using various methods and techniques. we used MTCNN and VGGface models for face detection and recognition. Customer information was stored in SQLite databases for identification purposes. We also used face matching to compare and determine the similarity between an uploaded or captured face image and the faces stored in the database. The streamlit Python package was used to input the uploaded image or camera images and to visualize the output of the system. Our system utilizes facial recognition to identify customers whose faces are stored in the insurance database. We applied various machine-learning concepts and Python libraries. This section typically provides a detailed explanation of the overall design and structure of the developed system. Figure 2 depicts the structure of the system.

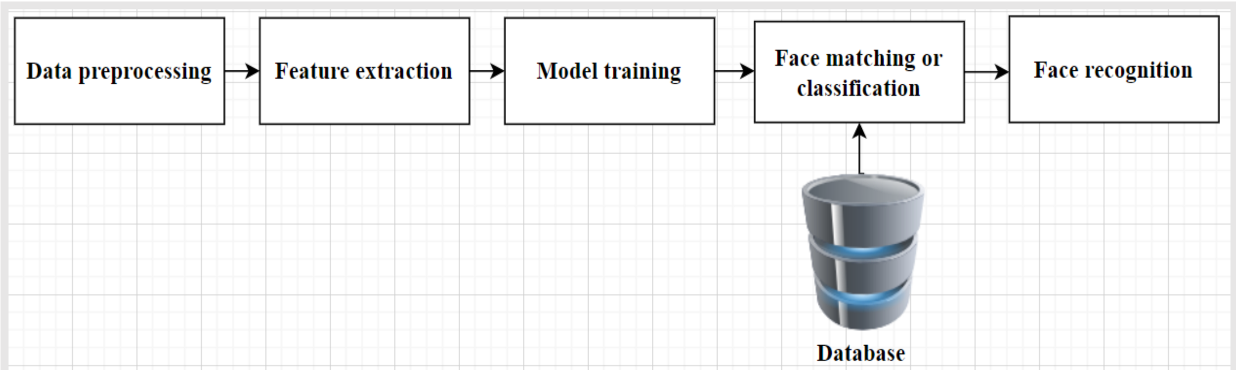

Fig. 2: System structure

➢ *Data Preprocessing:*

To change the default, adjust the template as follows Data preprocessing encompasses the initial steps required to prepare the input image for further processing. Within this module, the system enables users to upload an image containing a face for recognition, allowing them to provide their input for identification and verification.

Upon image upload, the system performs validation checks to ensure compliance with required specifications, including file format, size, and resolution. Additionally, the uploaded image undergoes face detection using the MTCNN algorithm, accurately localizing and aligning facial regions to facilitate subsequent processing stages. Once the faces are detected, face alignment is performed to normalize the face images and ensure consistency across different samples. It aligns the detected faces by adjusting their positions, rotations, and scales. Before feeding the aligned face images into the VGGFace model for feature extraction, preprocessing techniques are utilized to improve the quality and uniformity of the images.

➢ *Feature Extraction:*

Feature Extraction utilizes the VGGFace model to extract high-level representations of facial characteristics from the aligned regions. This module capitalizes on thecapabilities of the models to capture discriminative features. In our study, we used the cosine similarity metric to compare the facial features of the detected face with the features stored in the database. To extract facial features, we followed the steps outlined below:

- The images of the faces previously detected by the MTCNN model were passed through the VGGFace model.
- The model extracted 4096 features from each image.
- The extracted features were stored in a feature vector, where each dimension corresponds to a unique facial characteristic.

The extracted features, represented as a feature vector, were stored in the database for future comparisons and recognition tasks.

➢ *Model Training:*

To During the model training phase, we employed the MTCNN algorithm to detect faces in the images. Subsequently, the VGGFace model was fine-tuned using a labelled dataset to learn distinctive features for precise face recognition. The training process optimized the model's parameters through backpropagation and gradient descent algorithms. The VGGFace model learned to map input face images to a feature space where similar faces were closer together and dissimilar faces were farther apart. By leveraging the extracted features and labelled data, the training process aimed to enhance the accuracy of face recognition.

➢ *Face matching:*

Face matching involves comparing and matching the extracted facial features of a detected face with the features from different images of the same individual stored in the database. We set a similarity threshold of 55% for face matching, which means that a face is considered a match if the cosine similarity score is above the threshold value.

➢ *Face recognition:*

The system uses face-matching techniques to compare and match facial features for reliable identification. It calculates the similarity between input and known faces, displaying identification based on learned features. The flowchart in Figure 3 illustrates the overall process of the system.

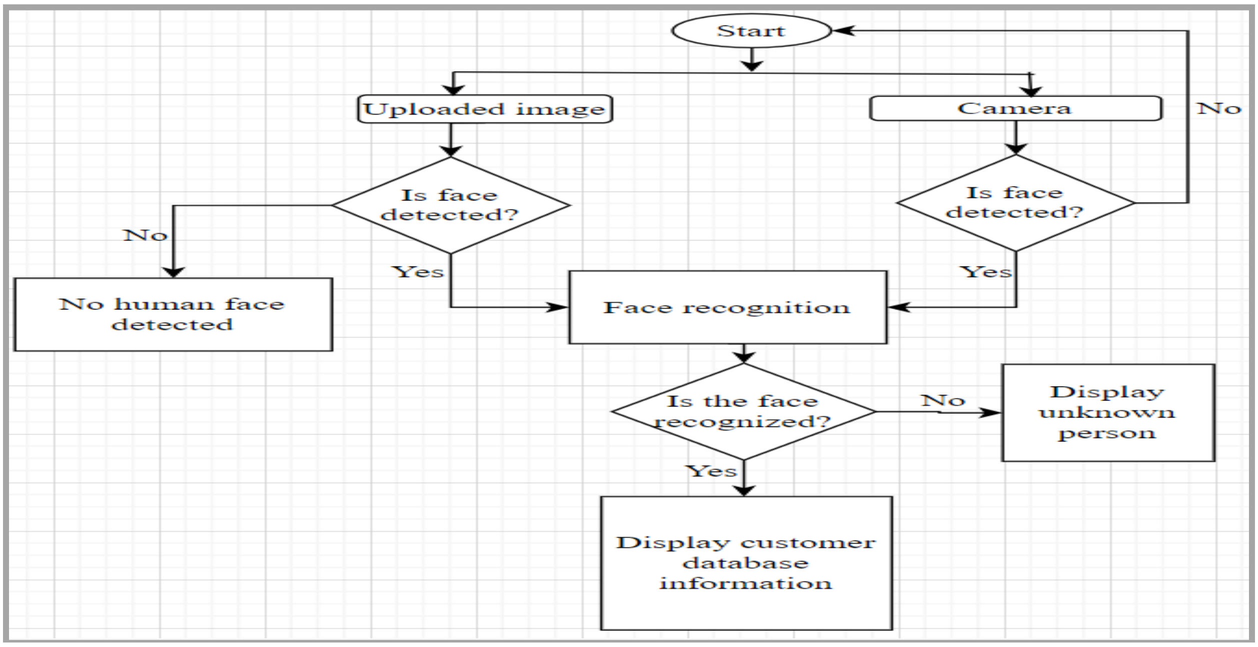

Fig. 3: Flowchart diagram of customer face recognition system

➢ *Performance validation:*

Several authors employed various evaluation measures to assess the performance of their models. While most studies utilized multiple indicators, a few relied on a single metric. In our face recognition system, we evaluated the validation model using four metrics: precision, recall, F1 score, and accuracy. These metrics provided a comprehensive assessment of the performance of our system. The evaluation was conducted on a test set of 100 images, and the results were recorded in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). These measures were employed to measure the dissimilarity between the predicted output of the model and the actual output, as shown in Table 1.

Table 1: Testing Results for 100 images

No	Number of images	Is the image in Dataset?	Obtained Confidence Level	Threshold	True Classified	False Classified
1.	3	NO	0.35	0.55	TN	-
2.	5	NO	0.39	0.55	TN	-
3.	6	NO	0.41	0.55	TN	-
4.	2	NO	0.45	0.55	TN	-
5.	4	NO	0.49	0.55	TN	-
6.	2	YES	0.52	0.55	-	FN
7.	2	NO	0.58	0.55	-	FP
8.	12	YES	0.63	0.55	TP	-
9.	2	YES	0.65	0.55	TP	-
10.	15	YES	0.69	0.55	TP	-
11.	7	YES	0.71	0.55	TP	-
12.	1	YES	0.75	0.55	TP	-
13.	5	YES	0.76	0.55	TP	-
14.	4	YES	0.77	0.55	TP	-
15.	10	YES	0.79	0.55	TP	-
16.	7	YES	0.81	0.55	TP	-
17.	5	YES	0.82	0.55	TP	-
18.	1	YES	0.85	0.55	TP	-
19.	4	YES	0.87	0.55	TP	-
20.	3	YES	0.91	0.55	TP	-
Total	100					

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From the provided testing results, precision was found to be 0.97, indicating a high proportion of accurately identified positive instances among all instances classified as positive. Precision is calculated by dividing the true positives (TP) by the sum of true positives and all positive predictions, as shown in equation (1).

$$\text{Precision} = TP/TP + FP \quad (1)$$

Similarly, the recall of the model was determined to be 0.97, highlighting its ability to capture a highproportion of actual positive instances. It is given by equation (2).

$$\text{Recall} = TP/TP + FN \quad (2)$$

The F1 score, which balances precision and recall, was computed using the harmonic mean of these two metrics as 0.97, further emphasizing the model's balanced performance in accurately identifying and classifying individuals. Equation (3) represents a mathematical expression used for memory retrieval.

$$\text{F1\_score} = 2* Precision * Recall/Precision + Recall \quad (3)$$

Furthermore, the accuracy of the face recognition model was computed using the formula shown in equation (4).

$$\text{Accuracy} = TP + TN/TP + TN + FP + FN \quad (4)$$

With the found values from Table 1 of TP = 76, TN = 20, FP = 2, and FN = 2, the accuracy was determined to be 0.96. This indicates a high level of overall correctness in identifying customers, considering both positive and negative instances.

The face recognition system validation model showed high precision, recall, and F1 score values, indicating its accuracy, reliability, and balanced performance. With an accuracy value of 0.96, it effectively improves customer service in insurance by accurately identifying individuals and streamlining identification processes. The system employs advanced deep learning algorithms (MTCNN, VGG-face) and a large training image dataset for enhanced reliability. By using cosine similarity and a 55% confidence threshold, only highly confident matches are considered true positives.

IV. RESULTS AND INTERPRETATION

Face recognition technology enhances customer identification and verification in insurance. The system accurately recognizes individuals, captures their faces, and securely stores customer information, enabling efficient data retrieval and improved customer service. The face recognition system integrates with databases, storing and retrieving customer information for efficient service delivery. It prevents errors, detects non-human faces, and ensures accurate and reliable identification, enhancing customer service accuracy and reliability.

Figure 4 displays the face recognition system's high accuracy in identifying customers, streamlining the identification process, and enhancing operational efficiency in customer service. It successfully matched faces with corresponding information from the database.

Fig. 4: Example of Customer Identification

Figure 5 demonstrates the strength of our system in detecting non-human images, preventing fraud and ensuring accurate customer identification.

Fig. 5: Detection of Non-Human Image

The experimental results validate the efficacy of the proposed face recognition system in enhancing customer service delivery in insurance companies. The high accuracy in customer identification and the system's ability to differentiate between human and non-human images contribute to improvedoperational efficiency, fraud prevention, and enhanced customer experiences.

The system uses a confidence level threshold to determine if a photograph belongs to a specific individual. This threshold, combined with cosine similarity, ensures that only highly confident matches are considered. The selection of 55% as the threshold value can be attributed to a trade-off between accuracy and strength. By setting a threshold of 55%, the system focuses on highly reliable matches, further enhancing the accuracy and precision of customer identification.

Upon recognizing a human face, the system retrieves and displays relevant customer information from the databases. This includes details such as name, ID number, age, address, associated insurance company, and recognition date. These timely information updates facilitate personalized customer service and enable insurance company employees to provide tailored assistance to customers.

The interpretation of these results indicates that the implementation of face recognition technology significantly improves customer service delivery in insurance companies. The system streamlines the identification and verification process, optimizes data capture and retrieval, prevents errors, and provides up-to-date customer information. By leveraging the benefits of face recognition technology, insurance companies can enhance their customer service efforts, leading to improved customer satisfaction and overall service quality.

The output of the proposed models detects and recognizes the faces. The accuracy of face detection can be categorized as true, false, or partially false. In our research, we evaluated the performance of various algorithms and found that the MTCNN and VGGFace methods outperformed other approaches. Table 2 provides a summary of the performance results achieved by these models.

Table 2: Model evaluation report

Model	Accuracy	Precision	Recall	F1-Score
MTCNN &VGGFace	96%	0.97	0.97	97%

The implementation of face recognition technology in insurance companies enhances customer service delivery and contributes to the body of knowledge in the field. In our study, feature extraction was achieved through the utilization of deep learning models such as VGGFace, MTCNN, and Facematch. These models were trained on a dataset of more than 10000 images from 102 customers. Feature extraction involved capturing the unique facial features of individuals, which were then used to create a representation of their faces in a high-dimensional feature space. This allowed for accurate matching and identification of individuals during the recognition phase.

The training of the datasets was conducted by feeding the images into the deep learning models. The models learned to extract discriminative features from the images, enabling them to differentiate between different individuals. During the training phase, the model's parameters were optimized to minimize the disparity between the predicted identities and the actual identities. This iterative process continued until the model achieved a satisfactory level of accuracy in recognizing and matching customer faces with their information in the insurance company databases.

This study makes a valuable contribution to the existing body of knowledge by demonstrating the effectiveness of CNN-based face recognition systems in enhancing customer service delivery in insurance companies. The use of deep learning models, such as VGGFace and MTCNN, enabled accurate and efficient face detection and recognition. The results of this study showed promising performance, with a high similarity score for uploaded images, as shown in Table 1. This indicates that the system was able to accurately match and identify individuals based on their facial features. In comparison to existing systems that exploit similar technologies, our study showcased several advancements. Table 3 shows the summary of other published work.

Table 3: Summary of previous work published.

Reference	Contribution	Model	Accuracy
This study	Developed a system for face detection and recognition	MTCNN and VGG Face	96%
[13]	Developed a system for joint face detection and alignment using MTCNN	MTCNN	95.4%
[14]	Developed joint-cascaded face detection and alignment	Cascaded CNN	95%
[15]	Developed a Multiview face detection system	Deep CNN	85%
[16]	Developed face detection system	CNN	92.27%
[17]	Developed boosted face detection system using Gaussian Feature	Haar-cascade Classifier	94%

This study utilizes face recognition techniques in insurance to identify customer information. Machine learning models are employed and a detailed comparison with previous studies is presented in Table 3, highlighting the advancements. Recent data testing confirms accurate face recognition and improved results. Integration of deep learning models like VGGFace and MTCNN enhances system performance, handling diverse facial characteristics. The system's reliability is reinforced by its ability to handle scenarios with unrecognized faces or non-human images.

V. RECOMMENDATIONS FOR FUTURE WORK

The face recognition system can be improved to provide better performance. One suggestion is to develop an Android application for more accurate detection and recognition of human images. This can be used in the underwriting process and for loss control, benefiting customers, insurance companies, and other companies.

Another recommendation is to regularly update the databases with new images of individuals, particularly those who are likely to change in appearance over time, such as children and young adults. This can help improve the model's ability to recognize individuals as their appearance changes. It is also important to remove or update images that may no longer be accurate representations of individuals, such as old images or images with poor quality. This can help ensure that the database remains accurate and up-to-date.

Future research could include exploring other state-of-the-art face recognition models to see if they yield better performance. Another area of research could be exploring ways to improve the system's strength to different lighting conditions, facial expressions, and poses. Additionally, research could be done on integrating the system with other modalities, such as voice recognition, to improve the overall user experience.

VI. CONCLUSION

The use of face recognition technology in insurance companies has shown great promise in enhancing customer service delivery. This study highlights the system's exceptional performance in accurately detecting and recognizing faces, securely storing customer information, and providing swift access to relevant data. By streamlining identification processes and enabling personalized interactions, face recognition technology has the potential to significantly improve operational efficiency and elevate the overall customer experience. The integration of advanced deep learning models like VGGFace, MTCNN, and Facematch has ensured reliable face recognition capabilities, including handling diverse scenarios such as unrecognized faces and images without human faces. The system's efficiency results in cost reduction and numerous advantages for insurance companies. It generates insurance information by identifying customer's faces and inputting data through the face recognition system, which is then transferred into the customer's face recognition system. Additionally, the system aids in identifying customers quickly,providing fast service, and helping decision-makers tackle the problem of lost or missing physical documents.

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