A Realization of Visual Biometric Validation to Enhance Guarded and Efficient Authorization for Intellectual Systems

Dmytro Dosyn, Taras Batiuk

Lviv Polytechnic National University, S. Bandera Street, 12, Lviv, 79013, Ukraine

Abstract

This research aims to delve into the realms of safeguarding enhancement and capability optimization within authorization procedures in intellectual systems through the utilization of visual biometric validation. The primary emphasis lies in progressing authorization systems by incorporating sophisticated biometric validation techniques. A specialized intellectual system has been developed, leveraging a paired neural network to launch guarded user authorization within the existing framework. In addition to incorporating fundamental safeguarding precautions such as hashing and guarded maintenance of access data, the contemporary importance of implementing two-aspect authorization is highlighted. This approach significantly bolsters user data protection, mitigating contemporary hacking techniques and providing a robust defense against potential data breaches. The two-aspect authorization system integrates face identification technology, employing visual biometric validation for heightened safeguarding compared to substitute two-aspect authorization techniques. Different realizations of the paired neural network, utilizing both the Contrastive loss approach and the Triplet loss approach, were scrutinized. Subsequently, a neural network employing the Triplet loss approach was implemented and trained. Following successful training and verification of the neural network's approach, it was seamlessly integrated into the intellectual system. This integration facilitated an efficient face identification mechanism for system users, preserving acquired information in the database and subsequently contrasting the current user facial data with the stored data throughout authorization. The result is a robust and guarded intellectual system that minimizes the risk of illegitimate access to user accounts, employing a useful and contemporary user authorization techniques.

Keywords

Multi-aspect authorization, visual biometric validation, paired neural network, face identification algorithms, Triplet loss approach.

1. Introduction

In connection with the rapid development and realization of intellectual systems, aspects of safeguarding and capability of the authorization process become particularly relevant and important tasks. The article aims to solve these problems by developing and improving authorization systems using advanced techniques of visual biometric validation and contemporary approaches to network learning. The key goal of this work is to create an intellectual system derived from a Paired neural network to ensure guarded user authorization. In addition to implementing basic safeguarding techniques such as hashing and storing logins and passwords, two-aspect authorization using face identification technology should be considered and implemented. This significantly increases the level of safeguarding and makes many contemporary hacking techniques impossible, which is actually the main part of the implementation of this work.

The purpose of the work is to improve authorization systems in intellectual systems using visual biometric validation. Advanced authorization techniques are considered and implemented,

COLINS-2024: 8th International Conference on Computational Linguistics and Intelligent Systems, April 12–13, 2024, Lviv, Ukraine
dmytro.h.dosyn@lpnu.ua (D. Dosyn); tbatjuk4u@gmail.com (T. Batiuk)
0000-0003-4040-4467 (D. Dosyn); 0000-0001-5797-594X (T. Batiuk)

in particular, a two-aspect system using face identification technology derived from a Paired neural network. The work is aimed at creating a reliable, safe and robust intellectual system that minimizes the risk of illegitimate access and ensures a high level of protection of user accounts. Having a general understanding of what exactly needs to be done within the scope of the work, the goal was divided into several main tasks. The main task is to create and train a model for face identification using Paired neural network technology. First of all, it is worth justifying the choice of a Paired neural network. A neural network is used because of its ability to efficiently compare two entities and produce vector forms for comparison. This is especially important for biometric validation tasks. Architecturally, a Paired neural network consists of two branches of the network that learn together, take two input images, and generate vector forms of the system user facial data. The Triplet Loss approach allows you to train the network so that the vector forms for one user are close, and for different users - distant.

Training and optimization also play an important role when using a dataset containing pairs of face images for training and testing, which must be optimized to adjust the model weights throughout training. After receiving the trained model, it is necessary to use a separate data set to validate the robustness of the model and determine the precision of face identification and the quality of the obtained vector representations. To successfully implement two-aspect authorization, with a focus on the technology of exploring, identifying and contrasting users' faces, several key steps and details should be considered. Specific system safeguarding and speed requirements must be defined. It is necessary to select a face identification technology for the realization of the second step of two-aspect authorization. Having an understanding of the chosen technology, it is worth creating a mechanism for exploring, identifying and contrasting faces, integrating it with the developed Paired neural network. An important part of the work is the realization of two-aspect authorization, where the first aspect is the login and password of the current system user, and the second is face identification. Having a working model of two-aspect authorization, it is necessary to optimize the already existing techniques of biometric validation, namely, to consider the latest achievements in the field of biometric validation and to choose the optimal means of authorization by improving the existing techniques of face identification to increase precision and speed.

The last important step is the integration of the neural network into the intellectual system, it is necessary to create an interface for the interaction of the neural network with the intellectual system and ensure the automated operation of the system that uses face identification for authorization and saving user data in the database. It should be taken into account that in addition to the general information about the user, it is necessary to store a photo of the user facial data and its aspects and to further compare the stored user photo with a picture from the user's web camera when logging into the intellectual system. It is necessary to take into account the peculiarities of working with relational databases, namely the principles of ACID - a set of characteristics that ensure the reliability of database operations, including atomicity, consistency, isolation and durability. Having a fully approachable system, it is worth evaluating and testing the system on various data and circumstances. Thanks to this, it is possible to collect data about the operation of the system and evaluate the precision and safeguarding of the system, taking into account possible attacks and challenges. Each of these steps is aimed at creating an robust and guarded authorization system derived from face identification and the use of advanced biometric validation techniques.

The entity of the research is the authorization system in intellectual systems, aimed at protecting information and ensuring high user capability. The article details the investigation of authorization techniques, including the use of visual biometric validation such as face identification and Paired neural network to achieve two-aspect authorization. The research entity extends to the development and optimization of an intellectual system, which includes the steps of processing and saving user data, face identification using a Paired neural network, and the realization of two-aspect authorization through the technology of exploring and contrasting users' faces. Also, the entity of the study is the capability and safeguarding of this system, in particular, the use of Contrastive Loss and Triplet Loss approaches to implement the Paired neural network, as well as the evaluation of the impact of this system on minimizing the risk of illegitimate access to the user account. The intellectual system includes authorization and safeguarding processes, in particular in the context of using visual biometric validation to recognize users' faces. The system is considered in terms of development and improvement of authorization techniques using advanced biometric validation algorithms. This entire involved process includes the creation and training of a Paired neural network, the realization of two-aspect authorization, the optimization of biometric validation techniques, the integration of the neural network into an intellectual system, the creation of a user face database, as well as the evaluation and testing of the developed system. Therefore, the entity of research is not only individual components of the system, but also their interaction and influence on the general process of ensuring safeguarding and capability of authorization in intellectual systems.

The subject of research in this work is the involved process of authorization in intellectual systems using visual biometric validation, in particular face identification, and the realization of a Paired neural network. Analysis and development of techniques aimed at ensuring safeguarding and improving the capability of the authorization process are carried out. The subject of the study is also two-aspect authorization, which includes the technology of exploring, identifying and contrasting the faces of system users. The use of visual biometric validation as a more guarded technique compared to other types of two-aspect authorization is considered in detail. Also, the subject of research is the Paired neural network itself, in particular variations of its realization using Contrastive Loss and Triplet Loss approaches. The focus is on developing, training, and integrating this network into an intellectual system to provide reliable user authorization.

The intellectual system, which will be implemented in this scientific paper, implements scientific innovation through the improvement and combination of advanced techniques in the field of biometric validation and machine learning. One of the key innovations is the use of a Paired neural network for face identification. This approach allows taking into account the unique features of each user, ensuring high precision of validation. The realization and training of a neural network using the Triplet Loss approach is an innovative step in the direction of improving biometric techniques. Also, the integration of face search, identification and comparison technology as a component of two-aspect authorization is an additional innovation. This increases the level of safeguarding, as the use of visual biometric validation becomes a more reliable and guarded technique of authorization. Scientific work also devotes attention to the optimization of biometric validation techniques using advanced algorithms and techniques, which contributes to increasing the precision and capability of face identification. The integration of all steps, including the development of a neural network, the realization of two-aspect authorization, the optimization of biometric validation and others, into a single intellectual system represents an innovative approach to solving safeguarding and authorization problems in intellectual systems. This complete scientific approach is aimed at creating an robust and reliable system that can minimize the risk of illegitimate access and ensure a high level of user safeguarding.

2. Related Works

The article [1] made an important contribution to the field of cyber safeguarding and automated susceptibility detection. The authors propose the use of graph neural networks for automatic assignment of Common Frailty Enumeration identifiers to susceptibilities. One of the key advantages of the article is the use of graph neural networks, which allows the model to robustly analyze the relationships amid various susceptibilities and their characteristics. The use of graph structures can improve the quality of susceptibility validation and classification. A well-written overview of existing techniques for detecting susceptibilities and assigning CWE identifiers indicates the authors' involved understanding of the domain. The proposal to use graph neural networks in the context of this task is original and promising. However, a more detailed discussion about the limitations and possible risks of using the proposed approach is desirable. Additional details on selected parameters of graph neural networks, training and different validation techniques will also improve the reader's understanding of the created model firmness and robustness.

The paper presents an innovative approach to the problem of susceptibility detection and automated assignment of CWE identifiers.

The work [2] proposes an innovative approach to the development of an intellectual system for socialization taking into account personal interests derived from SEO algorithms and machine learning techniques. The positive aspects of the article are the realization of the idea of using SEO algorithms in the context of a social network for user interaction. The use of machine learning techniques to analyze and recommend personal interests also indicates a high level of engineering competence of the authors. An illustrative overview of existing problems and the definition of a basis for the development of an intellectual system indicate a involved understanding of the subject area.

The presentation of information is structured and logical, allowing the reader to easily learn the concepts presented. However, attention should be paid to more specific details regarding the engineering realization of the intellectual system, such as the choice of machine learning algorithms, the justification of the choice of SEO algorithms and the importance of their use in this context.

The authors in the article [3] described the implementation of Paired Trackers derived from involved features for the task of visual monitoring. The authors highlight important aspects of using involved features and Paired models to improve the precision and capability of entity tracking in a video stream. The advantages of the article are the clear formulation of the problem and the expediency of choosing Paired Trackers for solving visual monitoring tasks. Special attention should be paid to the justification of the use of involved features, which allow to achieve high precision of entity tracking in variable circumstances. The authors thoroughly review various aspects of the realization of Paired Trackers, such as the architecture of involved networks, loss algorithms, and model updating techniques. This makes the article useful for researchers and practitioners interested in improving visual entity tracking algorithms. Finally, it should be noted that the paper could be even more valuable with further research aimed at contrasting Paired Trackers [4] with contemporary visual monitoring techniques and their robustness in different circumstances. This work is a significant contribution to the field of visual monitoring, where the use of Paired Trackers and involved features can improve results in real-world entity tracking circumstances.

In the article [5], an important aspect of the use of Paired neural networks in the tasks of regression and uncertainty quantification was considered. The authors propose a new approach to improve the performance of Paired neural networks by using similarity-based pairing. One of the key strengths of this work is the successful use of the idea of similarity to improve the precision and reliability of Paired neural networks in regression tasks. The authors analyzed the effect of different pairing techniques on the results and demonstrated that similarity-based pairing leads to improved performance of neural networks. An additional advantage of the article is that the authors study the use of Paired neural networks for uncertainty quantification, which is a current research area. They present interesting results and point to the possibility of using similarity to improve the reliability of uncertainty estimation in regression problems. The article is a valuable contribution to the development of the techniques of using Paired neural networks in regression and uncertainty quantification problems, and similarity-based pairing represents an robust approach to improving their performance.

The authors in the article [6] presented an innovative approach to detecting clones in Ruby code, using a Paired neural network derived from byte code. The authors thoroughly investigate the problem of detecting clones in software, which is an urgent task in the field of software development and maintenance. One of the key strengths of this work is the use of bytecode to represent Ruby code and the implementation of a Paired neural network to identify similarities amid pieces of code. This allows consideration of architectural and semantic aspects of clones, which can improve detection precision. An additional advantage is the realization of a Paired neural network technique for bytecode comparison, which can help identify more involved clone forms, such as altered clones, which are not easily detected using traditional techniques. The work also provides a sufficiently detailed overview of current techniques of clone detection, contrasting their advantages and disadvantages, which makes it useful for readers who are oriented in this field. The overall structure and presentation of the material in the work is clear and logical, which facilitates understanding of the techniques and results. Clearly defined steps of the experiment and the obtained results add weight to the proof of the robustness of the proposed technique. The article [7] presents an interesting and promising approach to detect clones in Ruby code using Paired neural networks derived from bytecode, and can serve as an important contribution to the field of software analysis.

The article [8] presented the problem of visual monitoring of entities and offers an robust and easy technique using the approach of differentiated search of neuro architecture. The work is focused on achieving high tracking capability with limited computing resources. One of the key strengths of this work is the use of the DNAS technique to automatically find the optimal neuro architecture for a visual monitoring task. This allows you to automate the process of choosing the optimal model, which is important for achieving high capability with limited resources. The article [9] describes in detail the process of differentiated neuro architecture search and model clarity approaches to ensure high performance in real time. The authors introduce robust mechanisms to reduce the volume and computational involvement of the model, which makes it suitable for use in variable circumstances. The achieved results indicate a high level of capability and speed of the proposed technique in comparison with other visual monitoring approaches. Experiments additionally confirm the competitiveness of the developed model.

The authors in the article [10] described the development of an robust system of recommendations taking into account reciprocity and popularity. The authors propose the use of a Paired Bi-Directional Gated Recurrent Units network to achieve this goal. One of the key advantages of this work is the use of the Paired Bi-GRU network to model reciprocity amid users and entities, taking into account their interactions over time. This allows taking into account the dynamics of relations amid users and entities, which is important in the context of recommender systems. The article includes a clear description of the techniques and models used, in particular, the Paired Bi-GRU network, which makes it easier for the reader to understand. Detailed analysis of experimental results and comparison with other approaches confirms the robustness of the proposed model in the circumstances of recommender systems. In addition, the work is devoted to taking into account the popularity of entities in the process of recommendations, which increases the realism and relevance of the recommendation system.

In the article [11], Paired neural networks were used for authorization derived from the dynamics of entering partial passwords. The authors set themselves the task of developing an robust authorization technique that takes into account the peculiarities of entering passwords by users. One of the significant advantages of this work is the use of the Paired neural network, which allows you to robustly work with small amounts of data and simulate the similarity amid the dynamics of entering different parts of passwords. This can be useful for authorization implementations where users tend to enter only a limited number of password characters. The article is clearly laid out and contains a high-quality analysis of the experimental results. A comparison [12] with other authorization techniques is made, which makes it possible to evaluate the robustness of the proposed approach. The implementation of the Paired neural network for solving the authorization problem derived from the dynamics of entering passwords is of interest and promising prospects. However, it should be noted that some aspects of the article could be considered in more detail, in particular, an explanation of specific choices of model parameters and a discussion of possible limitations and challenges in realization. In general, this work makes an important contribution to the field of authorization, especially in the context of using Paired neural networks to work with partial passwords and their input dynamics.

The authors in the article [13] described an innovative approach to the reproduction of dynamic visual perception using approachable magnetic resonance profiles and the Paired Conditional Generative Adversarial Network. The authors seek to solve the problem of reproducing visual impressions by analyzing the activity of brain regions recorded by fMRI. A significant advantage of this work is the use of Paired Conditional GAN, which allows you to robustly take into account the unique characteristics of each individual trial and generate high-quality visual reconstructions. Considering the involvement of the task of reproducing dynamic visual perception, the use of GAN can be a promising solution. The authors robustly demonstrate the results of the experiments and note the precision and realism of the reproduced visual impressions, respectively, of the datasets that were used to train the model.

The article [14] discusses the problem of detecting various breathing patterns derived from continuous human breathing signals using a one-dimensional artificial neural network and a classification technique for each type of breathing. The authors propose a new approach aimed at expanding the possibilities of detection and classification of various breath samples. One of the significant advantages of the article is the use of a one-dimensional artificial neural network that can efficiently process sequences of breathing signals. The introduction of a classification technique for different types of breathing allows you to obtain detailed information and improve the precision of determining a specific pattern. Experimental results indicate high precision of detection and classification of various breathing patterns. The authors also provide a detailed justification [15] of the techniques and algorithms used, which helps the reader understand the mechanism of the system. It is noted that the article can be useful for practical significance in medical diagnosis and monitoring of patients' health. However, limitations should be noted, such as the need for large amounts of training data and performance under variable patient physical activity. Overall, the work is original and can serve as a basis for further research in the field of respiratory pattern analysis.

The authors in the article [16] implemented an intellectual system for open classification of violations in power transmission systems. The authors propose a new approach that uses Paired networks to identify and classify different types of anomalies in electrical networks. One of the key advantages of the paper is the implementation of Paired sigmoidal networks for open classification tasks. The use of such networks allows you to robustly work with a large number of classes and adjust to new categories, which can be important in the real circumstances of operation of energy systems. The article [17] includes a clearly formulated statement of the problem, information about the neural architectures used, and techniques that provide clarity for engineers and researchers who may be interested in this area. The experimental results presented in the article confirm the robustness of the proposed approach. Paired sigmoid networks show a high level of classification precision and can be applied to detect new anomalies in power systems. It should be noted that the work examines real scenarios of violations in power transmission systems, which strengthens the applied significance of the presented approach. However, limitations such as the need for large amounts of annotated data and computational resources to train involved models should be noted.

The article [18] described the use of involved learning to recognize biometric parameters of wrist vessels. The authors use a large amount of data on wrist vessels to train involved neural networks and create a model for biometric face identification derived from the unique features of the vessels. One of the main advantages of this study is the use of involved learning to recognize the features of vessels, which can improve the precision of validation. The technique used in the article allows you to automatically determine and analyze the unique characteristics of blood vessels, which makes it robust and promising. The researchers provide clearly defined steps and techniques used to create and train the model. This provides [19] detail and clarity for the reader seeking to understand the techniques and techniques used. However, it should be noted that in some cases, low quality or small amount of training data can affect the robustness of the model. More experiments with different data sets and volumes are necessary for an overall evaluation of the firmness and precision of the system. Involved neural networks have the potential to significantly improve contemporary techniques of biometric validation, and research of this kind can have a practical appearance for the realization of biometric information systems in various technological areas.

In the article [20], the authors implemented entity identification in circumstances of a limited amount of training data, in particular in the context of underwater entity identification. The authors use a Paired neural network to solve the problem of limited data and improve identification precision. One of the main advantages of this research is the robust use of a Paired neural network for training on a small number of examples. The technique allows taking into account the limited amount of available data [21], which is relevant in the real circumstances of collecting information under water. The paper clearly describes the techniques and steps involved in training a Paired neural network, providing clarity and completeness for readers interested in implementing similar architectures in their own research. However, it is important to note that some engineering aspects, such as the justification of the choice of specific parameters and architectural solutions, can be more detailed. Additional explanations may improve understanding of the choices made by the authors and assist other researchers in adjusting a similar approach to their tasks.

3. Materials and Techniques

In the course of the work, it is necessary to distinguish two main goals of the scientific work, firstly, it is the creation, training and testing of a Paired neural network, which must perform two main tasks, namely, exploring for a face in a user's photo, and contrasting two photos in order to determine the correctness of the user who trying to log in. Secondly, it is the realization of the created neural network inside the intellectual system [22] and setting up its robust operation as a two-aspect user authorization module.

The Paired neural network is a special class of involved neural networks designed to solve comparison tasks. Its name arose from the similarity with the structure of "Paired twins", which have common roots, but individual characteristics. The main idea behind a Paired neural network is to learn the similarity or difference amid two input patterns. Paired network architecture includes two or more similar subnets that contribute parameters. Each of these subnets processes a separate input sample, extracting its key features. The output forms are then compared to determine similarities or differences amid the input data. One of the main implementations of Paired neural networks is visual comparison tasks, such as face identification, entity detection, or solving tracking problems.

The Paired network architecture allows studying neural forms to determine the degree of similarity amid two input samples, making it robust for comparison and classification tasks. We use an input layer succeeded by a 2D convolutional layer and the 2D pooling layer [23]. The data is then smoothed and a compression layer is added to created model. To ensure optimal performance of this layer, its values are normalized. The size of the all amount of entities is 128 units. When merging these two models, we use the scalar product of entities. Since the features are already normalized, their values are in the range 0 to 1, which allows us to easily compare them to the target labels. Figure 1 shows the encoding model and Figure 2 shows the model of the full Paired neural network.

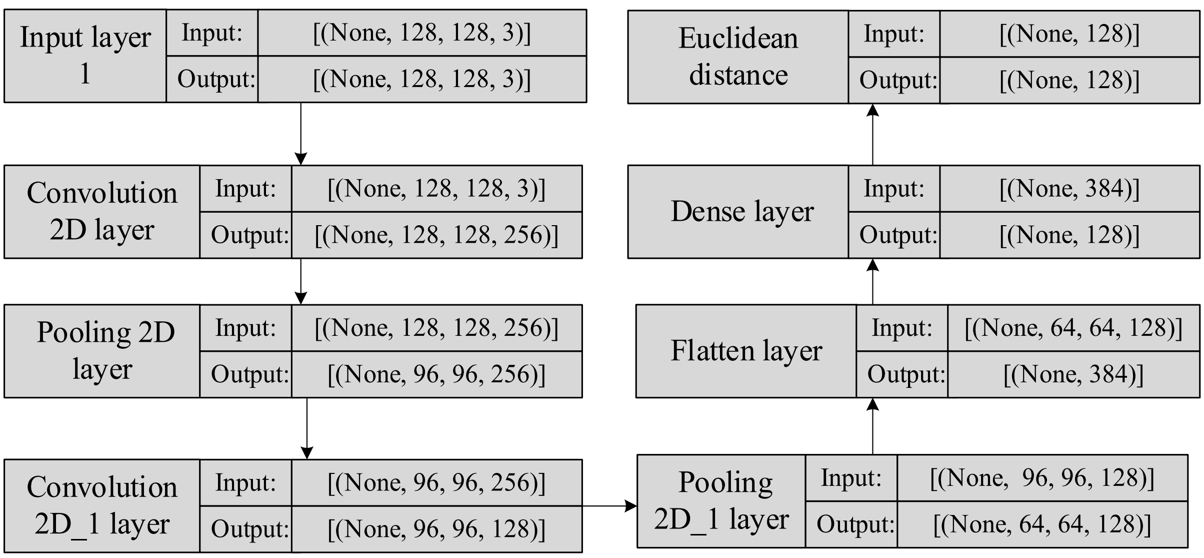

Figure 1: Neural network encoding model

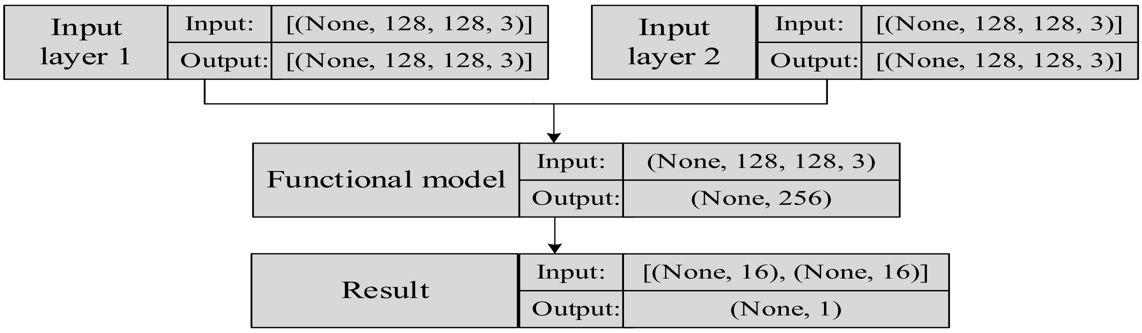

Figure 2: A model of a complete Paired neural network

In the course of work, it is necessary to select the main loss calculation approach, the basic option for use is the Contrastive loss approach [24], which is used in the Paired neural network to train the model on pairs of input samples. The main goal is to bring the vector forms of similar samples closer together and the vector forms of dissimilar samples further apart. The contrast loss approach determines the loss for pairs of images in such a way that it is minimized if the images are similar and maximized if they are different. It usually uses the concepts of "positive" and "negative" pairs, where positive pairs consist of similar or similar samples, and negative pairs consist of different ones. The contrast loss approach can be defined in various ways, but one popular option is to use the Euclidean distance amid vector forms of images. Typically, the loss for positive pairs tries to make the Euclidean distance as small as possible and for negative pairs as large as possible, thus providing efficient training for vector representations. The contrast loss approach is determined by formula 1, where D_w is defined as the Euclidean distance amid the outputs of adjacent neural networks, the calculation of which is given in formula 2.

$$Loss\ (P, N) = (1 - Y)\frac{1}{2}(D_w)^2 + (Y)\frac{1}{2}\{\max(0, m - D_w)\}^2, \tag{1}$$

$$D_w = \sqrt{\{G_w(X_1) - G_w(X_2)\}^2}, \tag{2}$$

The contrast loss approach has some drawbacks that should be considered, it is sensitive to hyper parameters, i.e. the robustness of the contrast loss approach may depend on hyper parameters such as the distance amid positive and negative samples, which needs careful tuning. To train the contrast loss approach robustly, it is necessary to have some balance amid positive and negative pairs, which can be difficult to achieve in real data. A large number of pairs to compare can lead to a significant computational burden, especially for large data volumes and involved models. The results of the contrast loss approach can be significantly altered by the quality of the vector forms provided by the model. If the model does not robustly learn useful features, then the results of the loss approach may be inadequate. With a large number of classes, it is difficult to select robust pairs for comparison, which can lead to less robust learning.

4. Experiment

Therefore, for robust work, it is worth using a more contemporary approach, such as the TLA (Triplet Loss approach [25]) - this is one of the types of loss algorithms that is often used in Paired neural networks for training models to compare entities in vector space. The basic idea of triplet loss is to ensure that vector forms of similar entities are close together, while vector forms of different entities would be separated in space.

The loss approach accepts three samples: both a positive and a negative sample for a particular entity, as well as a negative sample for another entity (trivially negative). The goal is to reduce the distance amid the vector forms of the positive and the anchor (trivially negative) pattern and, at the same time, to increase the distance amid the vector forms of the anchor and the involved negative pattern. Figure 3 shows a conceptual model of the Triplet Loss approach, which contains a key input [26] (anchor), as well as positive and negative entities at the input, and Figure 4 shows a Paired neural network model with an added Triplet Loss approach.

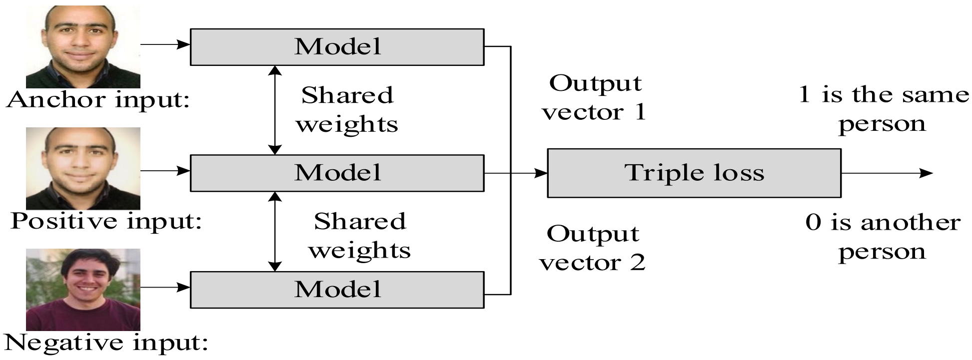

Figure 3: Conceptual model of Triplet Loss approach

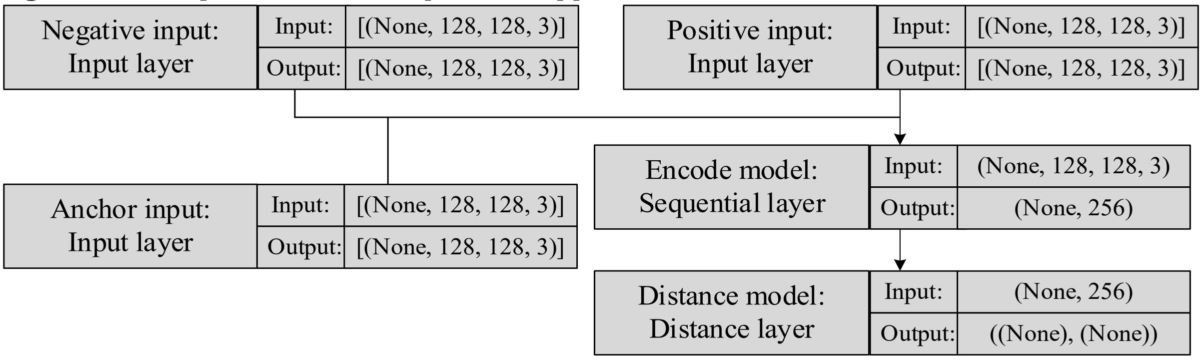

Figure 4: Paired neural network model with added Triplet Loss approach

The resulting vectors are passed to the distance layer, where the distance amid (binding, positive) and (binding, negative) pairs is calculated. In this context, we use a special layer to calculate the distance amid the current feature vectors [27]. This layer takes into account the distance amid the vectors and generates a response that serves as the basis for further steps, such as training the model to ensure efficient comparison of entities. The calculation of the vectors of the negative and positive samples is given in formulas 3 and 4, and the calculation of the Triplet Loss approach is also given in formula 5.

$$n = \|f_i^a - f_i^n\|_2^2, \tag{3}$$

$$p = \left\|f_i^a - f_i^p\right\|_2^2, \tag{4}$$

$$Loss\ (A, P, N) = max(\|f(A) - f(P)\|^2 - \|f(A) - f(N)\|^2 + \alpha, 0), \tag{5}$$

where A is an anchor (positive) sample, P is a positive sample (the same class as A), N is a negative sample (different class), f is an approach that defines the vector representation of the entity, α is a parameter that defines the minimum distance amid the positive and negative sample. Paired neural networks with Triplet Loss approach have many advantages, namely capability in dealing with limited data, i.e. limited training data, because they use three images for training instead of pairs.

The model [28] can learn to generalize features that are important for separating different classes or instances of input data. The Triplet Loss approach helps in solving the similarity and dissimilarity problem in the feature vector space by reducing the distance amid positive pairs and increasing the distance amid negative pairs. The model can be used for a variety of tasks, such as face identification, entity extraction or pattern identification, which is just right in our situation, since we need one final format for working with user photos and extracting user faces. There are also certain disadvantages of the Paired neural network with a Triplet Loss approach, namely, the model can be sensitive to the choice of hyper parameters, such as the size of triplets and parameters of the Triplet Loss approach, which may require additional tuning, which is not critical within the limits of the intellectual system being created, since will process photos that are reduced to one type, which will be initially configured using a separate implementation of a new neural network module in accordance with the current task and algorithms that were selected for further work.

As well as the dimensions of each layer and the input parameters of the Paired neural network with a Triplet Loss approach are given in Table 1.

Table 1
Outline of the Paired neural network model

Layer	Size	Parameters
Convolution	96 x 11 x 11	Steps = 1
Pooling	128 x 2 x 2	α = 10-5, β = 0.7
Dropout	-	k = 2, n = 2
Convolution	256 x 5 x 5	Steps = 2
Pooling	96 x 2 x 2	Steps = 1, applied series = 2
Dropout	-	α = 10-5, β = 0.8, k = 2, n = 2
Convolution	384 x 3 x 3	Steps = 2, applied series = 2
Pooling	64 x 2 x 2	Steps = 2, p = 0.35
Dropout	-	α = 10-5, β = 0.9, k = 2, n = 2
Fully loaded 1	1024	p = 0.45
Fully loaded 2	128	p = 0.55
Hidden embedding	128	Steps = 1

Additionally, in scenarios involving a substantial volume of data [29], the challenge of selecting robust triplets for learning may emerge, potentially leading to an increase in computational involvement. However, this aspect is not a significant concern within the current system, where only two photos are processed for a single user at a time—the current photo captured by the user's web camera and a photo stored in the database. In the event of improper triplet selection throughout training, an issue may arise where the model is inadequately trained. Conversely, like many other models, Paired neural networks may be susceptible to overtraining [30], particularly when dealing with limited data. This consideration becomes crucial throughout the realization of Paired neural networks, influencing both network architecture decisions and dataset selection for robust model training. Striking a balance amid the involvement of the model and the available data is pivotal to achieving optimal performance and avoiding issues related to undertraining or overtraining. Figure 5 shows the detailed structure of the Paired neural network with Triplet Loss approach, the size of each layer and its input parameters.

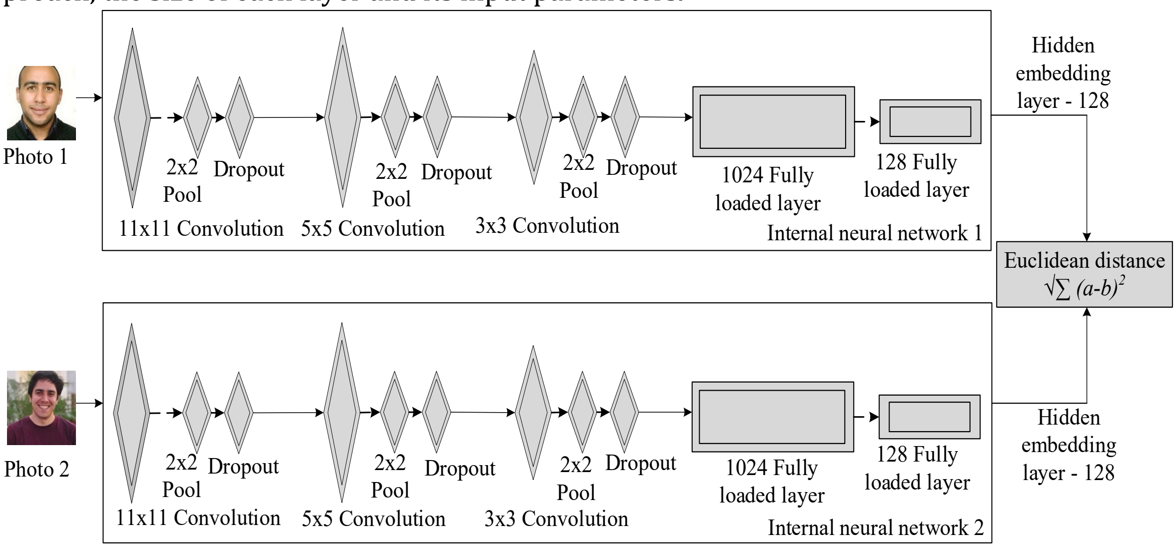

Figure 5: Detailed structure of a Paired neural network

Figure 6 shows a block diagram of the approach of the initialization of two-aspect authorization of the user in the intellectual system by taking a photo, exploring for a face, and then saving the media key in the database.

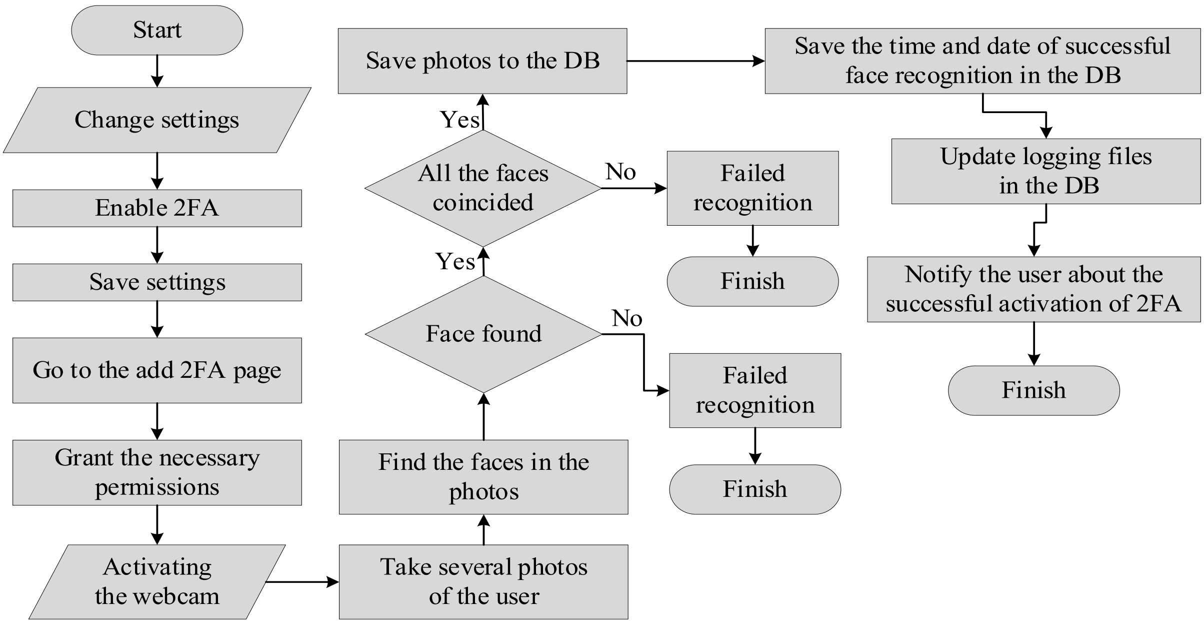

Figure 6: Initialization of two-aspect user authorization in an intellectual system

Figure 7 shows a diagram of the user authorization process, namely, validation of the entered login and password, saving in local maintenance the user's photo taken with the help of a web camera, and contrasting the current photo with the one already available in the database containing the user facial data, in case of a successful match signs, the user of the intellectual system gets access to the available approach.

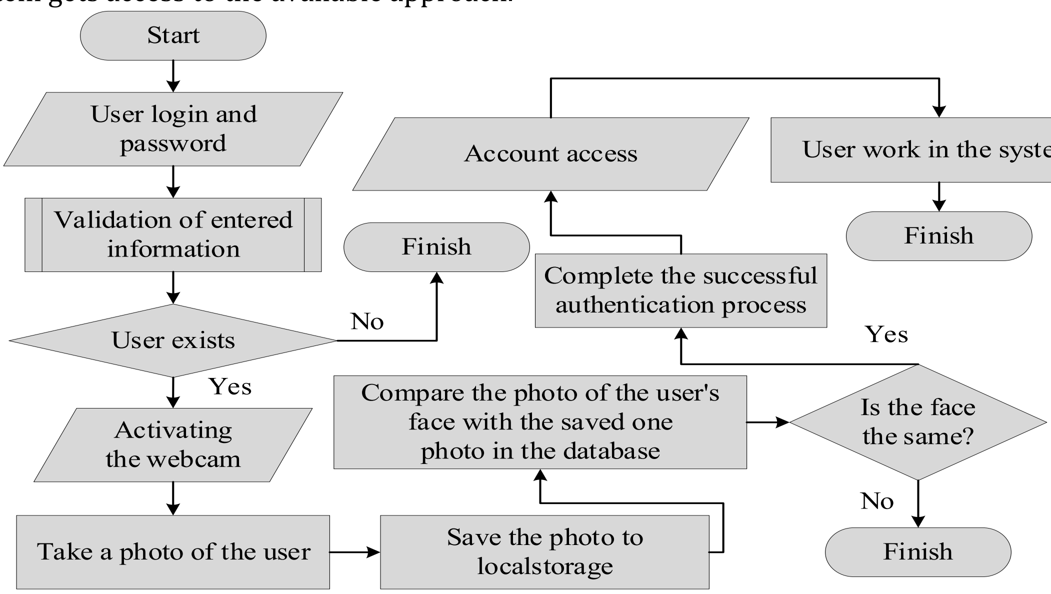

Figure 7: User authorization process

Figure 8 illustrates a sequence diagram within an intellectual system, delineating the interactions among three principal entities: the user, the server, and the database. Their communication is facilitated through HTTP requests, with each request possessing a distinct context derived from its type and synchronization properties, executed in a specific order. The diagram provides a visual representation of the dynamic flow of interactions, showcasing the orchestration of actions among these entities throughout the authorization process. As the user initiates actions, such as submitting login credentials or capturing a photo with a web camera, corresponding HTTP requests are generated and transmitted to the server. The server, in turn, processes these requests and interacts with the current database to retrieve or store all needed relevant information.

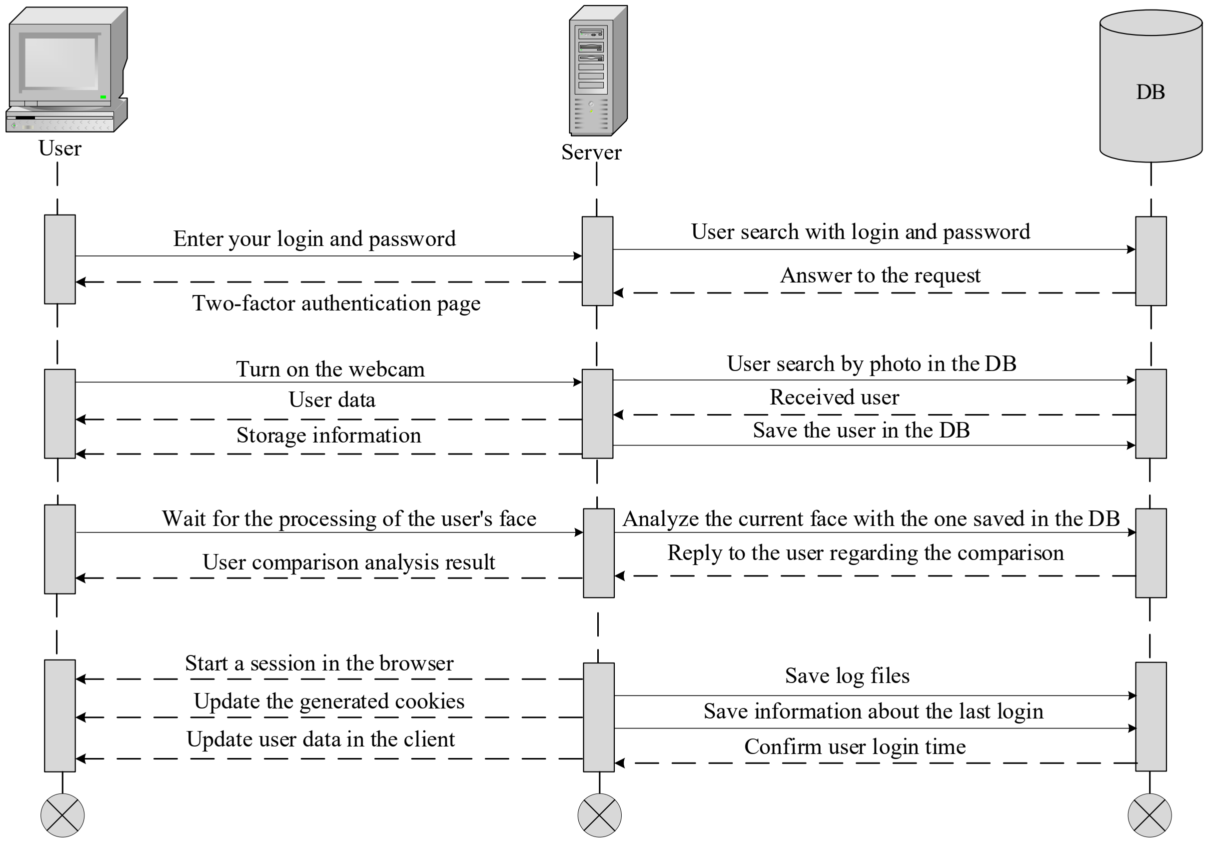

Figure 8: Sequence diagram of an intellectual system

The sequential arrangement of these interactions reflects the systematic execution of authorization procedures within the intellectual system and serves as a valuable tool for understanding the intricacies of the communication flow among system components, offering insights into the step-by-step progression of activities throughout the authorization process.

5. Results

Throughout the research process, a pivotal entity is the development of a Paired neural network, subsequently integrated into an intellectual system following rigorous testing. The realization leverages the Python 3.10 programming language for machine learning tasks, and the PyCharm IDE was selected as the coding environment. The initial step involves acquiring a dataset comprising photos paired with corresponding user labels, serving as the foundation for training and evaluating the neural network. The dataset encompasses 5000 images, featuring 50 distinct elements representing users. Each user is depicted from various angles and emotions, contributing to the diversity of the dataset. The images are standardized to dimensions of 128 by 128 pixels, portraying users against a black background in grayscale. The pixel values are normalized within the 0 to 1 range. User identifiers range from 0 to 49, ensuring unique validation within the dataset. Figure 9 provides a complete overview of the dataset, encapsulating critical information such as the total number of images, unique user elements, and the pixel dimensions of each image. Training precision evaluation metrics are also depicted, contributing to an understanding of the dataset and model performance.

```
There are 5000 images in the dataset          Accuracy score:0.93
There are 50 unique targets in the dataset    Average precision score, micro-averaged over all classes: 0.95
Size of each image is 128x128                 Distance:3.06
X shape: (500, 4096)                          Average Precision (AP): 1.0
X_train shape: (250, 4096)                    Average Negative (AN): 0.283
```

Figure 9: Information about the created neural network model

The following program approach is used to display 10 face images for each specified unique identifier. The images are displayed in the form of a grid, where each row represents one user from the dataset, and for each subject, 10 of his photos of different types are displayed, in which the user facial data is depicted differently and displays all unique emotions, this is shown in Figure 10.

Figure 10: Unique images of user faces from the dataset

Another, the information is reformatted, where each picture from the dataset is changed over into a one-dimensional cluster of measure 4096 * (128 * 128). The preparing and test datasets are shaped by isolating pictures from the starting dataset. In expansion, a DataFrame is made that contains subject IDs for the preparing dataset. DataFrame is the most data structure utilized within the pandas library for information preparing and examination. It makes a two-dimensional cluster of information, comparative to a table or information sheet, where the information is organized into columns and columns. Each row within the DataFrame compares to one test within the preparing dataset. This plays an important role for assist ponder and examination of conditions in the midst of subject identifiers and properties and markers within the neural framework. The another step was to create triplets for utilize in a Combined neural framework. A approach was composed that takes three contentions: the way to the picture catalog, a lexicon where the keys are the organizers (classes) and the values are the number of records in each envelope, and the most extreme number of records to consider for each envelope. An purge list was made to store the triplets and a list of all organizers (classes) inferred from the lexicon keys of the envelope list. Executed tuples for the stay and positive picture within the current organizer at the required files and parsed a variable for the negative picture organizer that's at first equal to the current envelope. Tuples for positive and negative pictures were chosen and all triplets were included to the common list. At the conclusion, the program approach returns a list of all made triplets.

Figure 11 illustrates a plot depicting the projection of individuals' faces onto a plane through the implementation of the principal component analysis (PCA) technique. Within this graphical representation, every point corresponds to the facial features of a specific individual. The plot is delineated by two axes representing the first two principal components, pivotal in determining the primary directions of variability inherent in the facial images. The X-axis aligns with the first principal component, while the Y-axis corresponds to the second principal component. Each point on the plot signifies the facial characteristics of an individual, offering a visual representation of the diversity among faces within the sampled dataset. The proximity of points on the plot denotes facial similarity, with close points indicating likeness, while greater distances reflect increased facial diversity. The utilization of distinct colors serves to differentiate individuals, and each color is associated with specific identifiers. This color-coded approach enhances the visual clarity and facilitates the clear segregation of different individuals within the dataset.

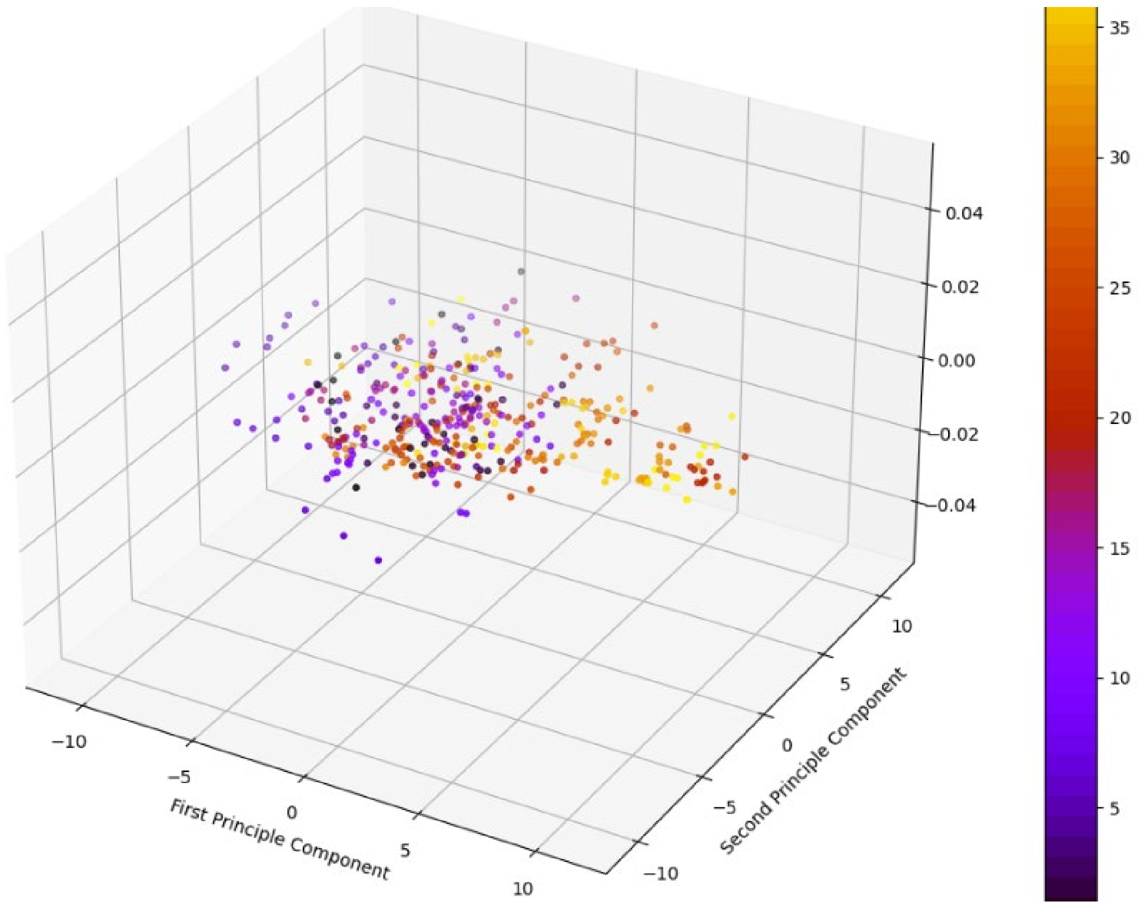

Figure 11: The plot of the projection of people's faces onto the plane

Next, it is vital to characterize different calculations and models for the realization of a Combined neural framework with a Triplet Loss approach. An approach was made to recover a bunch of picture triplets that acknowledges a list of triplets, the number of triplets in each group, current boolean values, and whether the picture ought to be preprocessed. Calculating the number of steps to get all bunches of triplets, initializing the records for the stay, positive, and negative pictures within the current bunch, and getting the grapple, positive, and negative pictures for the current triplet. Pictures for each category (stay, positive, negative) were included to the comparing list. A bunch of triplets in (128, 128, 3) arrange reasonable for utilize in a neural framework was gotten. After composing an approach to get a show of picture coding (a include extractor), a lesson was actualized to calculate separations in the midst of coded pictures.

Upon launching an approach to acquire the image coding model, the subsequent step involved implementing an approach to derive a Paired neural network derived from the coding model and incorporating a specialized distance layer. The resultant Paired neural network model underwent thorough testing and evaluation. Figure 12 provides insight into the classification results through the feature extractor technique, leveraging the distances amid encoded images. The graphical representation in Figure 12 introduces a discrepancy matrix, facilitating the assessment of the model's classification performance. The matrix is structured with user face numbers positioned horizontally and vertically, corresponding to distinct faces within the dataset. Each cell in the matrix denotes the count of faces that were accurately (on the diagonal) or inaccurately (off the diagonal) classified. The coloration of each cell serves as an indicator of the received quantity of faces classified for the specific image pair, distinguishing amid the anchor class and the predicted class. Darker colors signify a higher count of faces within the corresponding class. The matrix serves as a valuable tool for assessing the model's proficiency in classifying individual faces, providing a complete visual depiction of the classification outcomes. By analyzing the matrix, it becomes possible to discern the precision of the model's predictions for each specific face within the dataset.

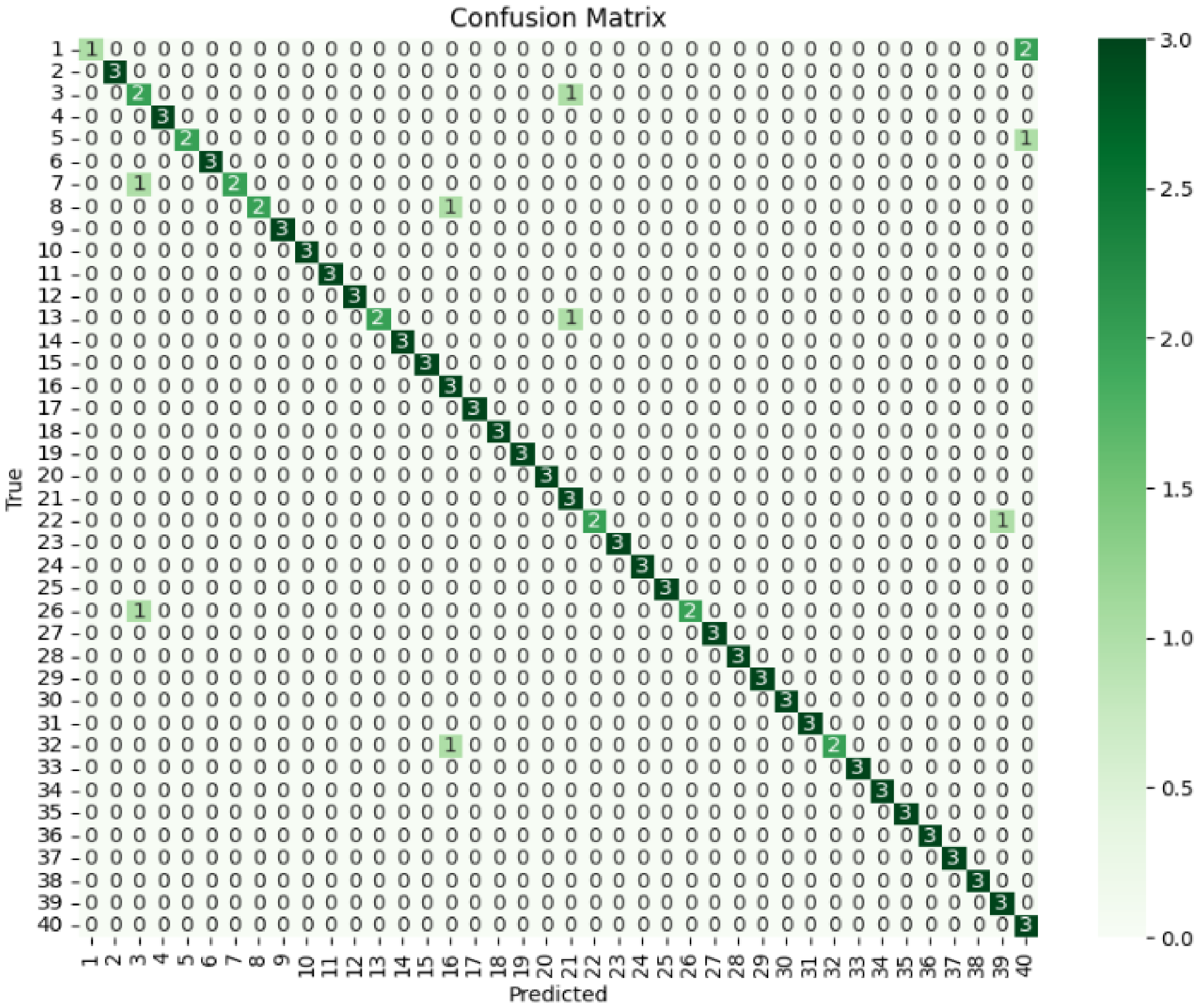

Figure 12: Discrepancy matrix for classification results

The another step was to announce a Combined neural framework show lesson, make a comparing lesson that acquires from the common information show lesson of the TensorFlow library, and characterize methods for preparing and testing the show, calculating loss, and initializing parameters. Having an substance of the Combined neural framework show course, an optimizer with certain parameters was characterized. The demonstrate was afterward completely gathered utilizing the required optimizer. Having a ready-made demonstrate, the approach of testing on triplets was characterized, which assesses the exactness of the demonstrate on test triplets, specifically, the accuracy on the test set of triplets and the normal values of the separations for adjust and incorrect sets are inferred. The required number of preparing ages was performed, specifically 512 ages. For each age, a calculation was made on the inferred esteem of the normal loss of the preparing set of triplets. The demonstrate is tried on a test set of triplets and measurements (accuracy, normal separations and standard deviations) are inferred. The demonstrate weights were saved when the exactness on the test set made strides, the ultimate preparing step was to spare the ultimate show weights after all ages. The by and large objective was to prepare a Matched neural framework employing a Triplet Loss approach to illuminate the errand of differentiating a client facial information in two photographs and deciding whether the reaction is positive or negative in a given context. The model tries to play down loss for rectify sets of client faces (grapple positive pictures) and maximize separations for off base sets of user faces (stay negative pictures). Figure 13 appears a plot speaking to a bend, where X-axis appears completeness, and Y-axis appears exactness. Each point on this bend compares to a certain choice limit for the classification demonstrate. Exactness decides what division of positive cases labeled by the show are correctly labeled, and completeness appears what division of positive cases which were really recognized by the already made show.

The precision-completeness curve indicates how precision and completeness change at different thresholds for solving the problem. The area under this curve indicates the quality of the model: the larger the value, the better. Also marked on the plot is the area amid the curve and the X-axis, which is colored purple and indicates the average precision score averaged over all classes. This number provides a generalized measure of classification quality by merging precision and completeness information for different classes. The higher the value of the average precision, the more efficiently the model works.

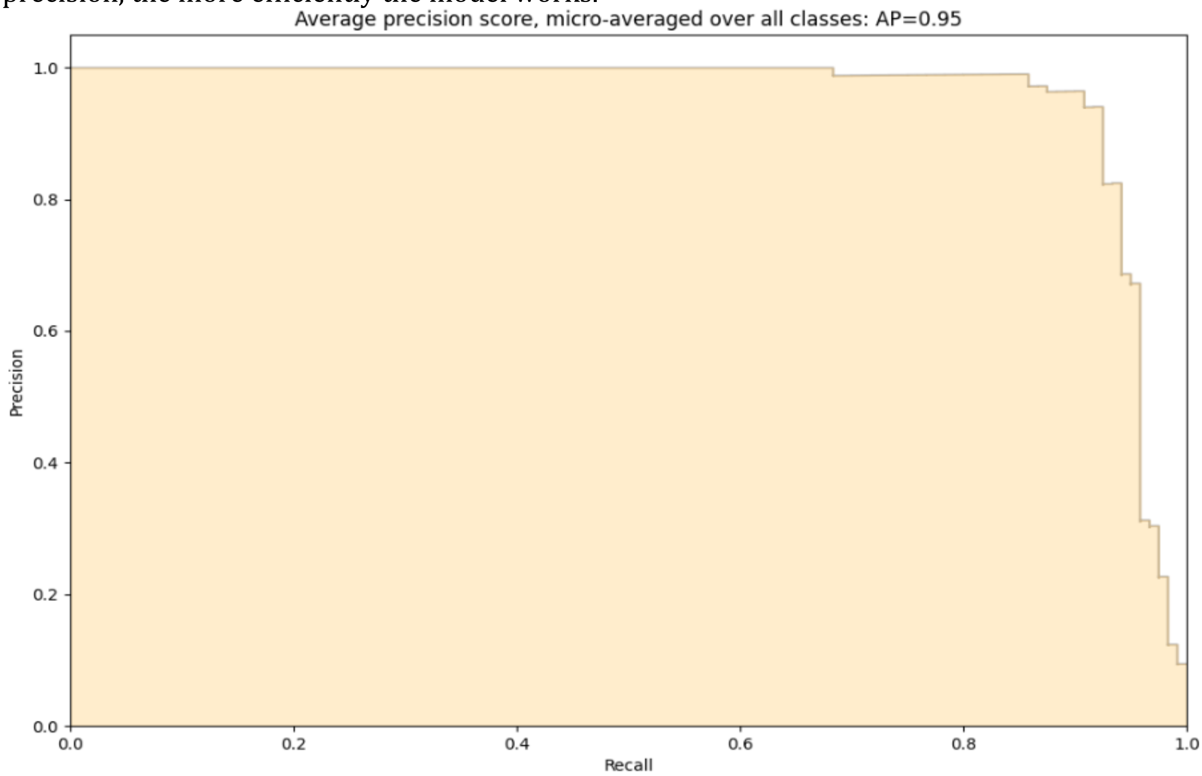

Figure 13: Changes in precision and completeness at different thresholds

Figure 14 appears an illustration of the comparison in the midst of the stay picture and the input closeness check approach, as can be seen from the plot, the two photographs contain the same client, so the expectation is positive. This plot comprises of three parts, the substance and structure of the primary and moment pictures and an picture appearing the absolute distinction in the midst of the primary and moment photographs utilizing color mapping. In this window, each pixel is spoken to by a shade concurring to the size of the distinction in the midst of the comparing pixels of the primary two pictures. Darker zones demonstrate less distinction, whereas lighter regions demonstrate more contrast. As a result, it is decided whether the photographs illustrate the same individual.

Figure 14: Determining whether both photos show the same person

Figure 15 shows the first step of user authorization in the intellectual system by entering a login and password, Figure 16 shows the basic two-aspect authorization start page.

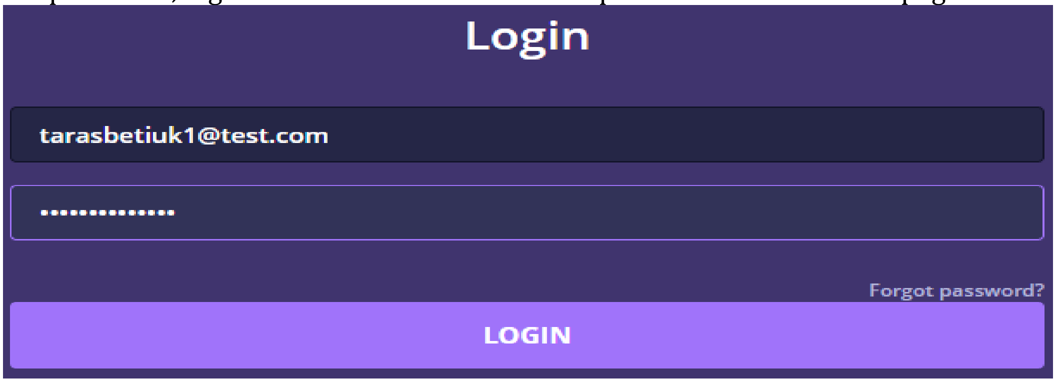

Figure 15: User input of login and password

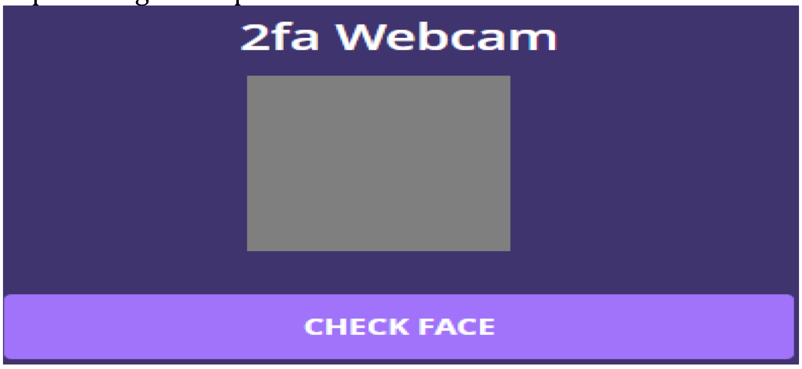

Figure 16: Two-aspect authorization home page

Figure 17 shows turning on the user webcam and taking a photo of the user facial data of the intellectual system, Figure 18 shows the process of processing the previously created Paired neural network photo and exploring for a face on it, and Figure 19 shows the result of a successful face search in the photo and highlighting a certain face in green the area of the image where the user facial data was found.

Figure 17: Taking a photo of the face of the current intellectual system user

Figure 18: Photo analysing process by Paired neural network

Figure 19: The result of a successful search for a face in a photo

Figure 20 shows a comparison of the user's current photo taken using a webcam and a photo stored in the database, as a result, the prediction of the Paired neural network is positive and the user has successfully authenticated to the system, also Figure 21 shows the current user's attempt to log into another user's account intellectual system, accordingly, the prediction of the neural network is negative and the user was refused authorization.

Figure 20: Successful authorization of the user into the intellectual system

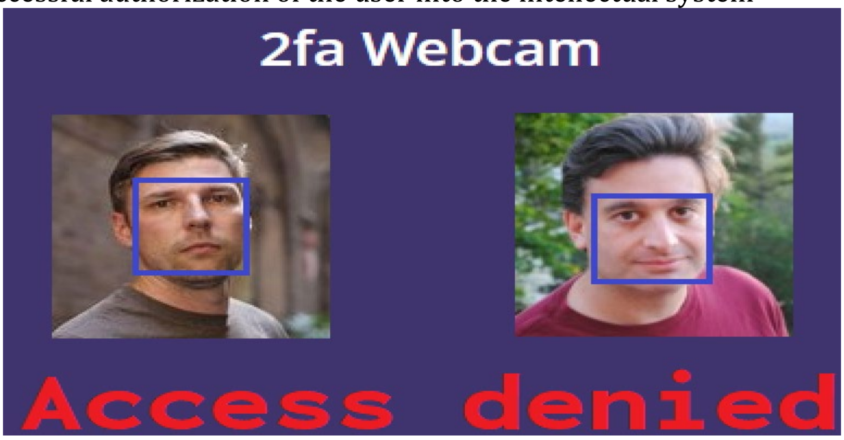

Figure 21: Refusing the user to authenticate to the intellectual system

So, throughout the presentation of the main research material, a Paired neural network with a Triplet Loss approach was implemented, which can both perform a general search for a user facial data in a photo, and compare two photos to determine whether they depict the same user. After training the neural network model and its subsequent successful testing with the help of the presented dataset, the modular integration of the created neural network into the intellectual system was carried out as an important aspect of the service of providing guarded login to the system, where it performs the approach of robust and reliable two-aspect authorization using visual biometric validation.

6. Discussions

A modern encoding approach was made determined from the source encoding esteem engineering. By going through the coding layers of the first demonstrate and replicating their weights to the comparing layers of the modern coding layer. The weights of the gotten encoded record were spared and a depiction of the engineering of the encoding layer was yield. After getting the embeddings for the transmitted records of confront pictures, the squared remove in the midst of the confront embeddings was calculated and classification was performed determined from the limit esteem, coming about in an cluster with expectations of or 1. Two records of forecasts (positive and negative) were gotten, which compare to comparable and diverse sets of client faces. All accessible test triplet bundles were tried and an picture classification approach was executed to get forecasts for positive (comparative) and negative (dissimilar) pairs of client faces. The ultimate step in testing the Matched neural framework with Triplet Loss approach was calling the measurements approach to assess and visualize the execution of the show.

The plot in Figure 22 speaks to the reliance of preparing loss on the number of cycles all through demonstrate preparing. Each point on the plot speaks to the loss at a particular emphasis. On the flat hub are the emphases, that's , the number of steps or ages of model training. The vertical pivot appears the loss values at each emphasis. The loss speak to the blunders of the show all through preparing. The plot shows a uncommonly chosen loss approach that can shift from emphasis to emphasis. In this case, a hyperbolic decrease of losses is connected within the beginning emphases (until a level is come to), after which the loss stay at a steady level. This plot makes a difference to heartily analyze the elements of loss all through show preparing and decide the vigor of the preparing handle.

Figure 22: Dependence of training losses on iterations throughout training model

The plot shown in Figure 23 displays the main metrics for the user face identification model. Average precision is a measure of how well the model recognizes positive pairs that should be similar. A high AP value indicates the robustness of the model in identifying similar faces. Average Negative - This value indicates the degree of similarity for negative pairs that should be different. A low AN value indicates the robustness of the model in identifying different faces. The last metric is test precision, which is the probability of a correct classification determination according to the test data set. The plot helps to evaluate three main aspects of the current model's performance for a specific determined face identification task.

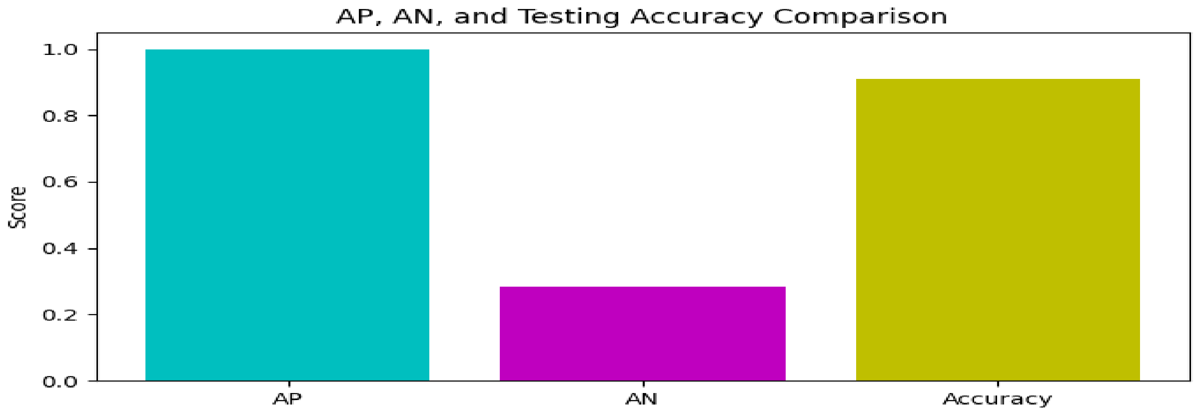

Figure 23: Evaluation of the main aspects of the capability of the created neural network

Critical insights into the training dynamics of the implemented Paired neural network showcased the current relationship amid training losses and the number of iterations. In essence, these visualizations serve as crucial tools for completely understanding the Paired neural network's behavior throughout training and its ultimate capability in the task of user face identification. The convergence patterns and metric evaluations depicted in these figures contribute valuable insights for refining the created model, enhancing its precision, and ensuring optimal performance within the intended implementation domain.

7. Conclusions

In the process of research and development of an authorization system derived from visual biometric validation using a Paired neural network, a complete analysis of aspects of safeguarding and robustness of the authorization process in intellectual systems was conducted. An important step in the research was a consideration of substitutes to the realization of the Paired neural network using the contrast loss approach and the Triplet Loss approach.

As a result of the analysis of already existing scientific works, the main advantages and disadvantages of the loss algorithms of Paired neural networks were determined and it was determined how exactly it is necessary to carry out the optimal integration of the neural network into an intellectual system. Therefore, the Triplet Loss approach was chosen as the optimal technique for training the model, which allows for high precision of user face identification. The main features of Paired neural networks were described using diagrams, and the operation of the neural network itself as a monolithic element and as a service in an intellectual system was also described. With the help of block diagrams and a sequence diagram, the system operation algorithm and http requests amid the system components were described. After carrying out the conceptual design, the program code was written, trained and tested a Paired neural network with a Triplet Loss approach, which has the approach of both exploring for a user facial data in one photo and contrasting several photos to determine whether a set of photos belong to the same user, which is an important requirement throughout the integration of a neural network into an intellectual system. In addition, the system was expanded with the approach of two-aspect authorization using the technology of exploring, identifying and contrasting users' faces. This not only increased the level of safeguarding, but also made the whole flow of the authorization process much more efficient and reliable.

The integration of the Paired neural network into the intellectual system made it possible to create an robust means of identifying the user facial data, storing and contrasting the received data throughout authorization. This approach minimizes the risk of illegitimate access and guarantees the safeguarding of user accounts. Therefore, the developed system is an robust and guarded tool for user authorization, capable of minimizing safeguarding threats in intellectual systems. This approach can be used to improve the protection of confidential information and ensure reliable system access control.

References

[1] X. Long, W. Zhuang, M. Xia, K. Hu, H. Lin, SASiamNet: Self-adaptive Siamese Network for change detection of remote sensing image, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 17 (2024) 1021–1034. doi:10.1109/jstars.2023.3330753

[2] J. Shu-hai, Z. Zhou, S. Sun, Loop Closure Detection Based on Compressed ConvNet Features in Dynamic Environments, Applied Sciences 14 (2023) 8–9. doi:10.3390/app14010008

[3] L. Li, Z.-H. You, S. Chen, L. Huang, J. Tang, B. Luo, GateFormer: Gate Attention UNet with Transformer for Change Detection of Remote Sensing Images, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 17 (2024) 871–883. doi: 10.1109/jstars.2023.3335281

[4] M. Ning, J. Tang, H. Zhong, H. Wu, P. Zhang, Z. Zhang, Scale-Aware Network with Scale Equivariance, Photonics 9 (2022) 142–143. doi:10.3390/photonics9030142

[5] T. Batiuk, D. Dosyn, Intellectual system for clustering users of social networks derived from the message sentiment analysis, Journal of Lviv Polytechnic National University "Information Systems and Networks" 13 (2023) 121–138. doi:10.23939/sisn2023.13.121

[6] Y. Zhao, X. Song, J. Li, Y. Liu, CSCNet: A Cross-Scale Coordination Siamese Network for Building Change Detection, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 17 (2024) 1377–1389. doi:10.1109/jstars.2023.3337999

[7] A. Farabbi, L. Mainardi, Domain-Specific Processing Stage for Estimating Single-Trail Evoked Potential Improves CNN Performance in Detecting Error Potential, Sensors 22 (2023) 9049–9049. doi:10.3390/s23229049

[8] L. Cheng, X. Zheng, M. Zhao, R. Dou, S. Yu, N. Wu, L. Liu, SiamMixer: A Lightweight and Hardware-Friendly visual Object-Tracking Network, Sensors 4 (2022) 1585–1585. doi: 10.3390/s22041585

[9] A. Kummerow, C. Monsalve, P. Bretschneider, Siamese recurrent neural networks for the robust classification of grid disturbances in transmission power systems considering unknown events, IET Smart Grid 1 (2021) 51–61. doi:10.1049/stg2.12051

[10] K. D. Apostolidis, K. Christos, K. Evangelos, E. Karampina, S. Moustakidis, D. Menychtas, G. Giarmatzis, D. Tsiptsios, K. Vadikolias, N. Aggelousis, Innovative visualization Approach for Biomechanical Time Series in Stroke Diagnosis Using Explainable Machine Learning Methods: A Proof-of-Concept Study, Information 10 (2023) 559–560. doi: 10.3390/info14100559

[11] T. Batiuk, V. Vysotska, V. Lytvyn, Intellectual System for Socialization by Personal Interests on the Basis of SEO Algorithms and Techniques of Machine Learning, in: CEUR Workshop Proceedings 4th Intern. Conf. on Computational Linguistics and Intellectual Systems, COLINS 2020, Lviv, Ukraine, 2020, pp. 1237-1250.

[12] Y. Gao, H. Wu, H. Liao, X. Chen, S. Yang, X. Han, A fault diagnosis method for rolling bearings based on graph neural network with one-shot learning, EURASIP Journal on Advances in Signal Processing 1 (2023). doi:10.1186/s13634-023-01063-6

[13] W. Mo, Y. Tan, Y. Zhang, Y. Zhi, Y. Cai, W. Ma, Multispectral Remote Sensing Image Change Detection Based on Twin Neural Networks, Electronics 18 (2023) 3766–3767. doi: 10.3390/electronics12183766

[14] S. Ally, S. Dowlut, M. Hamroun, K. Tamine, T. Anh, V. Petit, D. Sauveron, DFU-Helper: An Innovative Framework for Longitudinal Diabetic Foot Ulcer Diseases Evaluation Using Deep Learning, Applied Sciences 18 (2023) 10310–10311. doi:10.3390/app131810310

[15] H. Choi, Siamese Neural Network for User Authentication in Field-Programmable Gate Arrays (FPGAs) for Wearable Applications, Electronics 19 (2023) 4030–4031. doi: 10.3390/electronics12194030

[16] T. Batiuk, V. Vysotska, Technology for personalities socialization by common interests derived from machine learning techniques and seo-algorithms, Radio Electronics, Computer Science, Control 2 (2022) 53-63. doi:10.15588/1607-3274-2022-2-6

[17] H. Pang, M. Xie, C. Liu, R. Ma, L. Han, Siamese tracking combing frequency channel attention with adaptive template, IET Communications 20 (2021) 2493–2502. doi: 10.1049/cmu2.12280
[18] T. Basu, O. Menzer, J. Ward, I. SenGupta, A Novel Implementation of Siamese Type Neural Networks in Predicting Rare Fluctuations in Financial Time Series, Risks 2 (2022) 39-43. doi: 10.3390/risks10020039
[19] D. Yuan, Q. Li, X. Yang, M. Zhang, Z. Sun, Object-Aware Adaptive Convolution Kernel Attention Mechanism in Siamese Network for visual Tracking, Applied Sciences 2 (2022) 716-725. doi: 10.3390/app12020716
[20] D. Lee, J. Jeong, Few-Shot Learning-Based Light-Weight WDCNN Model for Bearing Fault Diagnosis in Siamese Network, Sensors 14 (2023) 6587–6593. doi:10.3390/s23146587
[21] M. Lei, K. Gao, H. Wang, Y. Liu, Z. Zhang, Z. Hu, X. Zhang, Focal Cosine Metric and Adaptive Attention Module for Remote Sensing Scene Classification With Siamese Convolutional Neural Networks, IEEE Access 10 (2022) 84212–84226. doi:10.1109/access.2022.3188652
[22] W. Li, C. Yang, Y. Peng, J. Du, A Pseudo-Siamese Deep Convolutional Neural Network for Spatiotemporal Satellite Image Fusion, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 15 (2022) 1205–1220. doi:10.1109/jstars.2022.3143464
[23] T. Batiuk, V. Vysotska, R. Holoshchuk, S. Holoshchuk, Intellectual System for Socialization of Individual's with Contributed Interests derived from NLP, Machine Learning and SEO Algorithms, in: CEUR Workshop Proceedings 6th Intern. Conf. on Computational Linguistics and Intellectual Systems, COLINS 2022, Gliwice, Poland, 2022, pp. 572-631.
[24] S. Ahmed, K. H. Lee, H. Y. Jung, Robust Hippocampus Localization From Structured Magnetic Resonance Imaging Using Similarity Metric Learning, IEEE Access 10 (2022) 7141–7152. doi:10.1109/access.2021.3137824
[25] J. Islem, F. Saïd, T. M. Hamdani, B. Neji, A. M. Alimi, Biometric-Based Security System for Smart Riding Clubs, IEEE Access 10 (2022) 132012–132030. doi: 10.1109/access.2022.3229260
[26] C. Song, S. Ji, Face Recognition Method Based on Siamese Networks Under Non-Restricted Conditions, IEEE Access 10 (2022) 40432–40444. doi:10.1109/access.2022.3167143
[27] R. Donida Labati, A. Genovese, E. Muñoz, V. Piuri, F. Scotti, G. Sforza, Computational Intelligence for Biometric Applications: a Survey, International Journal of Computing 15(1) (2016) 40-49. doi:10.47839/ijc.15.1.829
[28] I. Paliy, A. Sachenko, Y. Kurylyak, O. Boumbarov, S. Sokolov, Combined approach to face detection for biometric identification systems, in: 2009 IEEE International Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, Rende, Italy, 2009, pp. 425-429. doi:10.1109/IDAACS.2009.5342946.
[29] A. T. Hashim, Secure Verifiable Scheme for Biometric System based on Secret Sharing and CSK, International Journal of Computing 20(1) (2021) 78-84. doi:10.47839/ijc.20.1.2095
[30] Z. Guo, O. Arandjelović, D. M. Reid, Y. Lei, A Siamese Transformer Network for Zero-Shot Ancient Coin Classification, Journal of Imaging 6 (2023) 107–117. doi: 10.3390/jimaging9060107