Missing Person Identification System Using Deep Learning Algorithm (CNN) and Machine Learning Classifiers

M. Chenna Keshava, C. Srilakshmi Prasanna, V. Kavitha, K. Mahima, V. Padmavathi, and P. Srinivasulu

Abstract Missing our loved ones is the most painful situation. India, as the world's second most populated country, reports a countless number of missing person cases and many of those remain untraced. With the use of deep learning methods, a novel strategy is employed to locate individuals who have gone missing. People can upload images of shady people along with the necessary information to a common webpage. The submitted image is immediately verified to the registered images of missing people. The given input person image goes through a categorization process, and the image with the perfect match is chosen from the missing person database. Deep learning type is trained to accurately recognize the missing person photo in order to execute the selection task. Face recognition is performed using the convolutional NN and a robust deep learning method. Face descriptors are derived from photos using VGG-face deep architecture. The retrieved descriptors are matches with nearest missing person testing photos and classified using the KNN and SVM classifiers. The convolutional algorithm, unlike other deep learning methods, is utilized as a high-level feature extractor. The obtained outcomes are invariant to noise, light, contrast, occultation, pose, and the person's age because the best-performing algorithms were chosen. As a consequence, the results are obtained with a high degree of precision.

Keywords CNN · Deep learning · VGG-face · Face recognition · KNN · SVM

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1 Introduction

As a densely populated country, India records a significant number of missing person instances, many of which go unsolved. This paper describes a new model for detecting missing people that uses deep learning algorithms and machine learning classifiers [1–14].

The application will perform an automatic search of the entered photo among the missing person photographs. This aids policemen in tracking the missing individual in any region. The major goal is to compare and analyze the KNN and SVM classifiers. Our dataset has been used to train and test both classifiers. The accuracy of the training and testing processes, as well as the overall time spent on each, are calculated. The acquired values are compared, and the classifier with the largest accuracy and the shortest processing time is chosen. Finally, the user interface is linked to the chosen algorithm.

The visual geometry group (VGG) Facial models are a collection of face recognition algorithms developed by members of the University of Oxford's visual geometry group (VGG) and tested on common computer vision datasets. VGG Face and VGGFace2 are the two most popular VGG models for face recognition.

The K-nearest neighbor method is one of the most basic machine learning algorithms. It uses the supervised machine learning approach. The KNN technique considers that the new case/data and current cases are linked, and it assigns the new case to the category that is closest to the existing categories. As illustrated in Fig. 1, the KNN technique retains all available information and classifies new data points based on their similarity to current data. This means that the KNN technique can swiftly sort data into a well-defined category.

SVM is a supervised machine learning method that can be wield to solve classification and regression problems. However, it is mostly wield to solve classification task. In the SVM method, each data item is represented as a point in n-dimensional

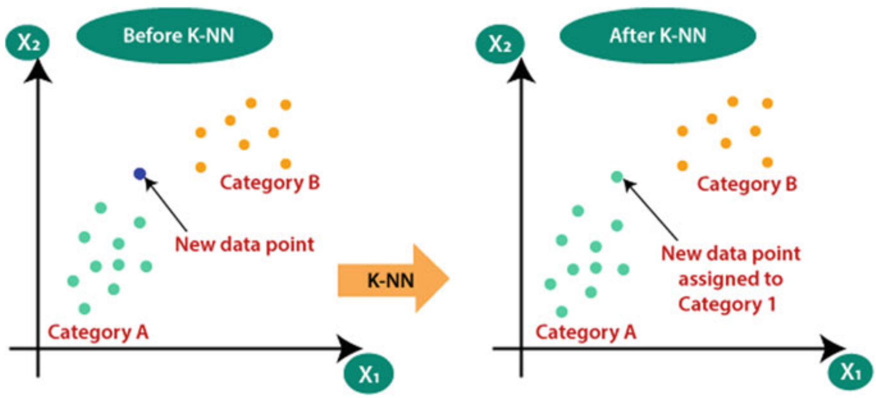

Fig. 1 Working of KNN algorithm

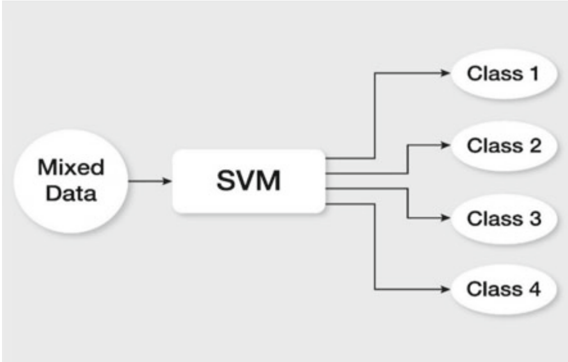

Fig. 2 Working of SVM algorithm

space, with the feature vector indicating the value of a specific position. The classification is then completed by identifying the hyperplane that clearly distinguishes the two classes, as shown in Fig. 2.

2 Literature Survey

The authors described principal component analysis (PCA) as an eigenface method for reducing the dimensionality of the original data space in their study [1]. PCA solves the recognition problem in a lower-dimensional representation space than picture space.

Linear discriminant method is an appearance-hinged technique for dimensionality reduction that has shown excellent results in face recognition, according to study [2]. The main disadvantage of using LDA is that it may run into the difficulty of a small sample size.

The scale-invariant feature transform (SIFT) recovers the key points (location and descriptors) for all database photos, according to the author of this work [3]. Then, given a changed image, SIFT extracts the image's main points and compares them to the dataset's points. To provide a feature description, the SIFT algorithm extracts the interesting key points from an image.

Speeded-up robust features (SURF) detectors are used to discover the interest spots in an image, and SURF descriptors are used to extract the feature vectors at each interest point, according to the authors of paper [4]. To lower the time cost of feature matching and computation, SURF uses 64 dimensions to encode the feature vectors at each interest point. To spin a sphere, the SURF approach is not stable.

The major goal of the research [5] is to look at using protection pursuit (PP) to reduce the complexity of a big number of users' support vector machine (SVM) classifier. The proposed method will aid in the accurate establishment of biometric identification systems for massive datasets. Preliminary results on the YALE face database indicated that the proposed strategy is effective in increasing user recognition rates while reducing SVM complexity.

The author demonstrated the consistent benefit of replacing the SoftMax layer with a linear support vector machine in article [6]. Deep learning using neural networks has claimed state-of-the-art outcomes in a wide variety of tasks.

Face recognition was the most extensively used for image analysis, according to the authors of research [7]. Its appeal stems from the fact that it has a wide range of business and law enforcement uses, as well as the availability of cutting-edge methodologies.

The authors of paper [8] offer a new database dubbed "ImageNet," a large-scale ontology of images built on the WordNet structure's backbone. ImageNet seeks to fill the bulk of WordNet's 80,000 synsets with 500–1000 clean, full-resolution images on average. The digital revolution has resulted in a massive data explosion. According to the most recent estimates, Flickr has over 3 billion photos, YouTube has a similar amount of video clips, and the Google Image Search database has an even higher number of images.

The paper [9] provides a method for identifying missing children that blends deep learning-based face feature extraction with KNN-based matching. Unlike most deep learning algorithms, their technique simply uses a convolutional network as a high-level feature extractor, while the trained KNN classifier does the child recognition.

The research study [10] focused on face detection system as well as two application fields: querying human beings and searching similar backdrops. The rest area application can be further divided into two scenarios: Querying human identification in general, such as photographs of people on the beach, and identifying specific individuals, such as photographs of Hilary Clinton giving a speech.

An innovative strategy to exact recognition and tracking of human faces in videos is presented in the publication [11]. The goal is to spread the information of a collection of seed faces that have been discovered offline with high certainty in order to recover faces that have been missed or detected with low confidence. In particular, their method generates a person-specific skin color model from the color of the seed face, which is then used to perform particle filtering for sequential face tracking. Then, to improve the overall smoothness of the localization findings, a backward propagation strategy is designed.

The paper [12] addresses a simple yet effective method for face recognition that makes robust use of histogram of oriented gradients (HOG) features. The following are the three primary contributions of this work: To begin, we propose extracting HOG descriptors from a regular grid to compensate for mistakes in face feature detection caused by occlusions, posture, and lighting variations. Second, by combining HOG descriptors at multiple sizes, significant structures for face recognition can be captured. Third, we determine that dimensionality reduction is required to eliminate noise and make the classification process less prone to overfitting.

3 Problem Statement

A notion is suggested for creating a virtual environment in which recent pictures of people submitted by family/relatives at the time of reporting missing cases are maintained in a repository. The public is encouraged to take images of people in suspicious situations and post them to the platform. This photo will be automatically searched among the images of the missing persons. This aids police officers in locating the individual in any location. When a person is located, the photograph taken at the moment is compared to the images posted by the police at the time of the missing person's abduction. Occasionally, the person has been missing for an extended period of time. This age gap is shown in the images as the shape of the face and the texture of the skin alter with age. It is necessary to use an age-insensitive feature discriminator. Position, orientation, lighting, occlusions, background noise, and other elements may all have an impact on a person's face appearance. The photograph shot by the public may not be of high quality, since some of them may have been taken from a remote location without the person's knowledge. To overcome these challenges, a performance comparison of SVM and KNN based on time and accuracy was conducted, and the most efficient method was employed to match the photos.

4 WorkFlow

The steps are followed to accomplish desired results are:

1. Training the dataset with suitable images.
2. Implementing the both SVM and KNN classifiers on the trained dataset.
3. Results comparison.

Almost 1000 images are collected from Internet and from our co-students and created a file folder for each person with the name of that person. Each folder contains at least two images of single person with at most age gap of 10 years. The path of these directories is given as training directory in the training function. Images which contain noises like age, brightness, position of person, etc., to make sure that algorithm is working fine with any type of images.

The performance of both SVM and KNN is tested by measuring parameters like accuracy and total time taken to execute the entire program. The resulted values are tabulated and graphs are drawn from those values. Using those graphs, the most efficient algorithm is obtained and used in the project to match the person images.

5 Results Analysis

Time and Accuracy at different number of images

The time and accuracy of SVM and KNN at 50 images are calculated. The time taken by the SVM is greater than the KNN. In Fig. 3, the time and accuracy of SVM and KNN at 100 images are shown. The time taken by the SVM is greater by 150 s than the KNN.

The time and accuracy of SVM and KNN at 150 images are evaluated. The time taken by the SVM is greater than the KNN. In Fig. 4, the time and accuracy of SVM and KNN at 200 images are shown. The KNN takes less time and both the SVM and KNN given approximately same rate of accuracy.

The time and accuracy of SVM and KNN at 250 images are calculated. The time taken by the SVM is greater than the KNN. Figure 5 illustrates the time and accuracy of SVM and KNN at 300 images are shown. The time taken by the SVM is much greater than the KNN to process 300 images.

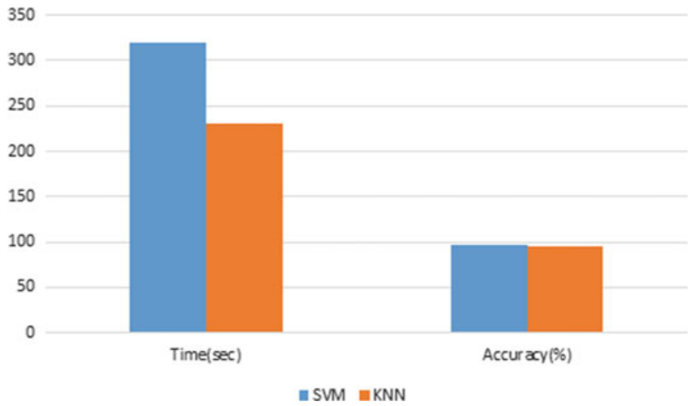

Fig. 3 Time and accuracy for 100 images

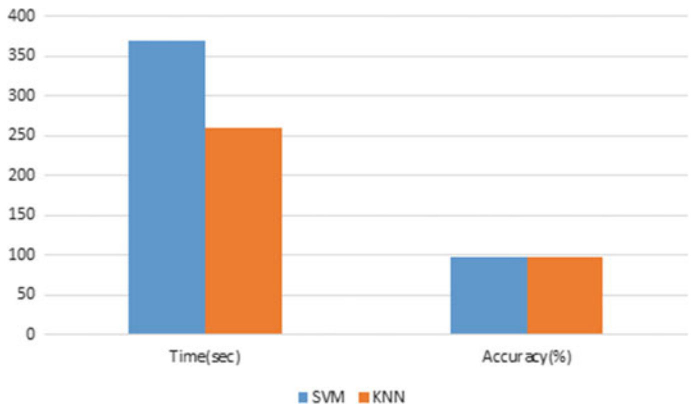

Fig. 4 Time and accuracy for 200 images

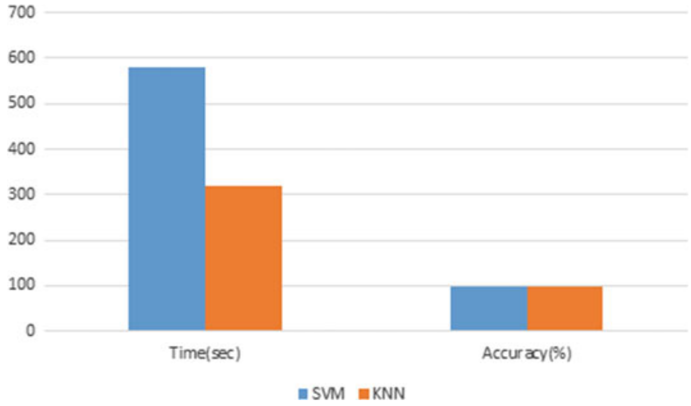

Fig. 5 Time and accuracy for 300 images

The time and accuracy of SVM and KNN at 350 images are evaluated. The time taken by the SVM is greater than the KNN. Fig. 6 shows the time and accuracy of SVM and KNN at 400 images. The time taken by the SVM is greater than the KNN.

The time and accuracy of SVM and KNN at 450 images are evaluated and compared. The time taken by KNN is lesser than the SVM. In Fig. 7, the time and accuracy of SVM and KNN at 500 images are shown. The time taken by the SVM is little greater than the KNN.

Table 1 shows accuracy rate in percentage of SVM and KNN at different number of images. The SVM accuracy rate is decreasing with increasing the number of images, whereas KNN accuracy rate is increasing with increasing number of images. The KNN algorithm achieves highest accuracy with large number of images when compared to SVM.

In Fig. 8, the accuracy of SVM and KNN at different number of images is shown. At first, i.e. from 50 to 150 images, SVM obtained a little high rate of accuracy. Then

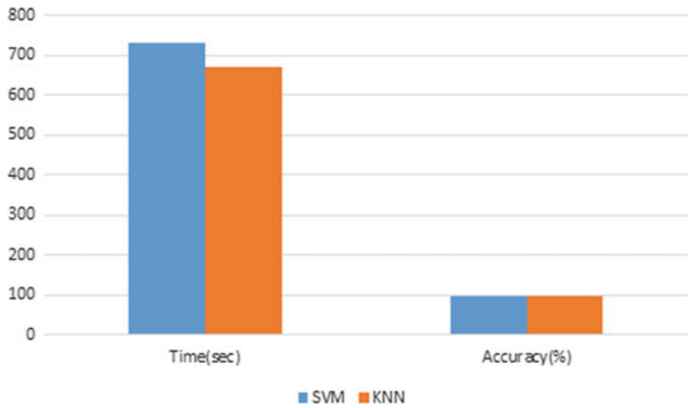

Fig. 6 Time and accuracy for 400 images

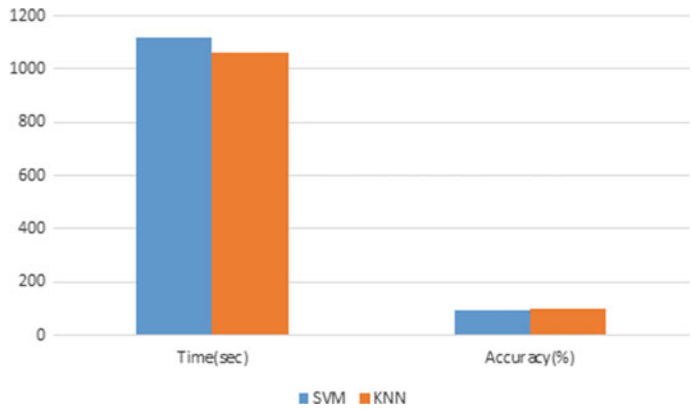

Fig. 7 Time and accuracy for 500 images

Table 1 Accuracy (in %) of SVM and KNN at different number of images

No. of images	Accuracy rate of KNN (in %)	Accuracy rate of SVM (in %)
50	90.0	95.0
100	95.0	97.0
150	96.6	98.3
200	97.5	98.7
250	97.7	97.8
300	97.8	97.7
350	97.7	97.2
400	97.6	96.2
450	97.0	96.2
500	97.0	96.8

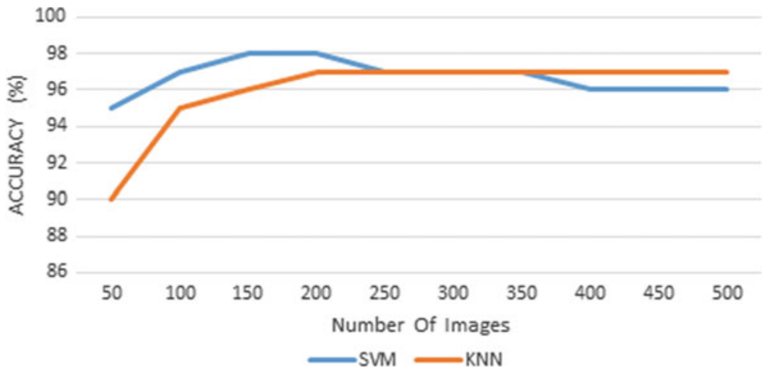

Fig. 8 Number of images versus accuracy for KNN and SVM

the number of images increased from 200 to 250 images both SVM and KNN have given same accuracy rate. But with increasing number of images, i.e. from 300 to 500 images, KNN showed a greater rate of accuracy.

Table 2 shows total time taken in seconds by SVM and KNN to give results at different number of images. The SVM takes more time to process than KNN. With increasing number of images, time taken by both SVM and KNN increases, but KNN takes less time when compared to SVM.

Fig. 9, the time taken by SVM and KNN at different number of images is shown. The time taken by the SVM is greater than the KNN.

Table 2 Time taken (in sec) by SVM and KNN

No. of images	KNN (Sec)	SVM (Sec)
50	169.88	288.35
100	232.00	314.37
150	240.30	345.88
200	260.65	367.06
250	280.85	397.17
300	320.70	582.37
350	500.48	684.72
400	670.92	732.44
450	860.92	932.45
500	1060.92	1120.26

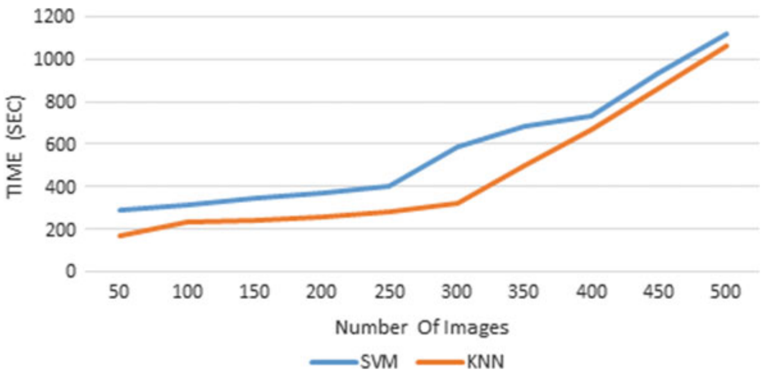

Fig. 9 Number of images versus time taken of KNN and SVM

6 Conclusion

A missing person identification framework is implemented, which combines an effective CNN-hinged deep learning strategy for feature extraction with KNN and SVM classifiers for categorical classification. The two classifiers are compared using different parameters that have been learned using human face feature representations. When compared to SVM, the KNN achieves higher accuracy in less time. As a result, KNN is integrated into the user interface in order to match missing person photos. The developed face recognition technology could be used to identify missing people in a convenient way.

References

1. Gumus E, Kilic N, Sertbas A, Osman NU (2010) Face recognition using PCA (principal component analysis). Expert Syst Appl 37:6404–6408
2. Bansal A, et al (2012) Face recognition using PCA and LDA algorithm. In: 2012 second international conference on advanced computing and communication technologies, vol 5. pp 251–254
3. Luo U, Ma Y, Takikawa E, Lao S, Kawade M, Lu B-L. Person specific SIFT (Scale invariant feature transform). J Appl Res Technol Versión Online 13. ISSN 2448-6736 versión impresa ISSN 1665-6423
4. Du G, Su F, Cai A, Face recognition using SURF features. Proceedings of SPIE—the international society for optical engineering, vol 4, pp 1–9. https://doi.org/10.1117/12.832636
5. Ghouzali S, Larabi S, Mislov A, Wilson C, Chen L (2020) Face identification based bio-inspired algorithms. Int Arab J Inf Technol 17(1):1–5
6. Tang Y (Feb 2015) Deep learning using linear support vector machines. International conference on machine learning 2013: challenges in representation learning workshop. Atlanta, Georgia, USA arXiv:1306.0239-v4-21, pp 6–9
7. Mishra1 S, Dubey A (Jan 2015) Face recognition approaches: a survey. Int J Comput Bus Res (IJCBR). 6(1):1–5. ISSN (Online): 2229-6166
8. Deng J, Dong W, Socher R, Li L, Li K, Fei-Fei L (2009) ImageNet: a large-scale hierarchical image database. 2009 IEEE conference on computer vision and pattern recognition, pp 248–255. https://doi.org/10.1109/CVPR.2009.5206848
9. Suman (Dec 2020) Nearest neighbor for missing child identification. Int J Eng Res Manage (IJERM) 07(12):49–58. ISSN: 2349-2058
10. Srihari R, Zhang Z, Rao A. Image background search: combining object detection techniques with content-based image retrieval (CBIR) systems 1:1–5. https://doi.org/10.1109/IVL.1999.781131
11. Tao J, Tan Y-P (2005) Accurate face localization in videos using effective information propagation. IEEE international conference on image processing 2005, pp 2-72. https://doi.org/10.1109/ICIP.2005.1530506
12. Déniz-Suárez O, et al (2011) Face recognition using histograms of oriented gradients. Pattern Recognit Lett 32:1598–1603-v2, 1–8
13. Iqbal A, et al (2021) Intelligent data-analytics for condition monitoring: smart grid applications. Elsevier, p 268. https://www.sciencedirect.com/book/9780323855105/intelligent-data-analytics-for-condition-monitoring. ISBN: 978-0-323-85511-2
14. Tomar A, et al (2020) Machine learning, advances in computing, renewable energy and communication, vol 768. Springer Nature, Berlin, LNEE, p 659. https://doi.org/10.1007/978-981-16-2354-7. ISBN 978-981-16-2354-7