**Auto-Attendance System using Face Detection and Recognition**

**ABSTRACT:**

In computer vision and machine learning, research on face detection and identification is expanding. Using the ResNet50 architecture as our basic model and a few additional layers of transfer learning, our goal in this research is to construct a face detection and identification model. Deep convolutional neural network ResNet50, which has demonstrated great performance in image identification applications including facial recognition, has been developed. To fine-tune a model for a particular job, we employ transfer learning, a technique in which we take a model that has already been trained and add new layers to it. In particular, we extend ResNet50 with new face recognition layers and optimise the model as a whole on a huge dataset of face photos. According to our findings, the improved ResNet50 model performs better on our face recognition challenge than the original ResNet50 model. As a result of the extra layers, we added to the model, face recognition is now more accurate and produces fewer false positives. The development of a face detection and identification model based on the ResNet50 architecture utilising transfer learning is demonstrated in our project as a successful method. Our concept has potential for usage in a number of applications, such as security systems, monitoring systems, and online advertising.

**KEYWORDS:**

Face detection, Face recognition, ResNet50, Transfer learning, Convolutional neural network

**INTRODUCTION:**

The development of more precise and effective models has sparked substantial breakthroughs in facial recognition technology in recent years. Due to the enormous diversity of faces in photographs, including variations in stance, expression, and lighting conditions, the work of facial identification is still difficult. Researchers have suggested employing deep learning methods, including convolutional neural networks (CNNs), to extract high-level characteristics from photos for face detection and recognition in order to overcome this problem.

With ResNet50, a deep CNN architecture that has demonstrated exceptional performance in image recognition applications, we are concentrating on creating a face detection and identification model in this project. We take advantage of the pre-trained ResNet50 model's existing weights and incorporate new layers made specifically for recognising faces to fine-tune the model for our particular job of facial recognition using transfer learning. We employ a dataset of face photos with a range of positions, expressions, and lighting conditions to train and evaluate our model. We divide our dataset into training and validation sets after pre-processing the images to detect and extract faces. Our ResNet50 model is adjusted via transfer learning on the training set, and its performance is assessed on the validation set.

Our findings demonstrate that the improved ResNet50 model outperforms the original ResNet50 model in our face recognition test, delivering higher accuracy and fewer false positives. This highlights the efficiency of utilising transfer learning to create a face detection and identification model based on ResNet50, which may have a variety of applications, such as security systems, surveillance systems, and digital marketing.

**Literature Review:**

**CNN:**

An image classification and object detection task-specific type of neural network is called a convolutional neural network (CNN). Convolutional layers are used by CNNs to identify the features and patterns in an image. The input image is subjected to a variety of filters in these layers, producing a number of feature maps that are then utilised for classification. CNNs also employ pooling layers to decrease the spatial dimensions of the feature maps and improve the network's computational performance. All of the neurons in the final layers of a CNN are normally fully linked, which means that they are all connected to every neuron in the layer above. The final classification choices are made by these layers using the characteristics that the convolutional and pooling layers have learned. Transfer learning is a typical strategy used by CNNs to increase performance on a particular task by fine-tuning pre-trained models on a fresh dataset. The ability of CNNs to learn hierarchical representations of the input data, automatically identifying and extracting features at various levels of abstraction, is the key to their success in image identification tasks.

Jayashree N C et al. [5] in 2022 proposed a model using Convolutional Neural Networks (CNNs) to detect and recognize face masks in real-time. The authors trained the CNN on a dataset of over 500 images with masks and without masks to classify the presence of masks in images. The model achieved a high accuracy rate of over 95% in detecting masks in real-world scenarios. The model is also capable of recognizing the type of mask being worn, whether it is N95 or a simple cloth mask. The authors conclude that the CNN-based model could be a useful tool in promoting mask usage and controlling the spread of COVID-19. One drawback in the paper is that the paper does not address privacy concerns related to the use of this model, such as the collection and storage of individuals' facial images.

Sushil Kumar Mishra et al. [6] in 2021, presented a machine learning based method for detecting face masks in images, using Tensorflow as the deep learning framework. The authors used a dataset of images with and without masks to train a convolutional neural network (CNN) to classify images as either "with mask" or "without mask". The network was tested on a separate dataset and achieved high accuracy in detecting masks. The approach can be used in real-time applications, such as surveillance systems, to ensure that individuals are wearing masks in public spaces during the COVID-19 pandemic. The limitations of the paper include using a small or imbalanced dataset, mainly focusing on evaluating the performance of the face mask detection system in controlled environments, and not evaluating the scalability of the approach.

In December 2021, Shanmuhappriya M et al. [7] proposed an automatic attendance monitoring system using deep learning methods such as DCNN. It used Max margin Object Detection and Histogram of Orientation Gradient for detection of face. The algorithm of FaceNet was used to extract some high quality features. The model is trained using KNN. The paper was only tested on small dataset and large dataset could give computational problems.

In January 2023, Wenjing Wang, et al. [8] proposed a novel approach for detecting faces in low-light conditions, where traditional face detection methods often fail. The authors propose an unsupervised learning approach that does not require labeled training data. The method uses a generative adversarial network (GAN) to generate synthetic face images in different lighting conditions, and then trains a CNN to detect faces in real images by comparing them to the generated synthetic images. The method was evaluated on a benchmark dataset and showed promising results, outperforming traditional methods in detecting faces in low-light conditions. However, the authors have not considered other unsupervised learning models or techniques that could perform better for face detection in low-light conditions.

Oleksandr Miakshyn et al. [9] proposed in 2021, a face recognition technology that focuses on improving the performance of face recognition systems using convolutional neural networks (CNNs). The authors propose a novel CNN architecture that incorporates multiple convolutional and pooling layers, followed by fully connected layers. The network was trained on a large face recognition dataset, and the results showed improved accuracy and robustness compared to traditional face recognition methods. The authors also evaluated the network on real-world face recognition tasks and achieved state-of-the-art performance, demonstrating the potential of CNNs in improving face recognition technology. However, the use of face recognition technology raises privacy concerns, as it involves collecting and storing large amounts of personal data. The authors may not have addressed these concerns in the paper, and further research is needed to address the ethical implications of using face recognition technology.

In the month of March, 2020 Sikandar Khan et al. [10] proposed a real time automatic attendance system using face API and OpenCV. The paper describes how RCNN is used to detect faces and how YOLO V3 algorithm is used for face detection. Microsoft azure is used as the face database. The model will take attendance twice to confirm who attended the class for the whole duration. OpenCV can have limitations for pose of the image and other features on a person’s face which results in wrong detection.

**Deep Learning based systems:**

A deep learning-based automatic attendance system automates the process of collecting attendance in offices, classrooms, and other settings by utilising computer vision and machine learning. Typically, a camera is used to take pictures or videos of people. Deep learning algorithms are then used to detect and recognise certain faces. The system can recognise and identify people with high accuracy since it can be trained on a sizable collection of labelled faces. Following storage in a database, the attendance data can be used for a variety of tasks, including keeping track of attendance records, creating reports, and determining grades based on attendance. Compared to conventional attendance methods, deep learning-based systems are more accurate, require less time and effort, and are more effective. However, the general deployment of deep learning-based attendance systems may be constrained by privacy issues and the requirement for high-quality training data.

Pinaki Ranjan Sarkar et al. [11] proposed in August 2019 automatic attendance system using deep learning framework. This paper used a state-of-the-art face detection model to detect the faces and a novel recognition architecture to recognize faces. There were mainly two steps involved: face detection and face recognition. For face detection the paper proposed a novel deep learning framework to find small and tiny faces which was found to be very effective. The face detection algorithm worked very well for classroom images. After detecting the, a cropping operation was performed and the facial images for each frame were stored. For face recognition, a model was proposed that recognizes faces using self-alignment learning. The limitation in the paper was mainly due to the limited training data, as it used only 25 frames to evaluate the proposed framework and only faces from first 20 frames for training the framework, but deep learning models require a large amount of data to be trained effectively.

In the year 2019, Joshan Athanesious J et al. [12] proposed the Deep Learning Based Automatic Attendance System. Problems like occlusion and different lightning scenarios were solved in the paper. Also, user interaction was reduced in the model used which is DPAAS. The work of this paper won't work where workstation class desktop and servers are unavailable. Multiclass identification problems were overcome by the model used in the paper.

Sourav Mandol et al. [13] proposed in December 2021 a real-time face recognition system that also detects liveness to prevent against spoofing attacks. The system uses OpenCV, a computer vision library, and deep learning techniques to accurately detect and recognize faces. The liveness detection component of the system is designed to distinguish between real faces and fake faces created using photos or videos. The authors evaluate the system on a dataset of real and fake faces and show that it achieves high accuracy in both face recognition and liveness detection. The authors conclude that the system can be used for a variety of applications, such as secure access control and payment authentication, to ensure the security of personal information and financial transactions.

Kunjal Shah et al. [14] proposed in August 2021 an Automatic Attendance System based on face recognition that marks the presence of students by detecting their faces against its trained set, from the image of everyone sitting in the classroom. It made use of the Haar Cascade classifier to detect faces by recording some of the features of the images like eye, nose etc. The students are first added to the database, after which the algorithm takes a region of interest from each student's face image and resizes it to a fixed size. The facial photos of the students in the class are compared to the features that are kept in the database. The database records the required students' attendance. The proposed system is subject to various limitations in the paper: It cannot tolerate noise; as a result, noisy photos will result in a reduction in overall accuracy. Additionally, a sufficient number of classifiers should be cascaded to increase speed. To address the vulnerability to assaults, proper security measures are necessary.

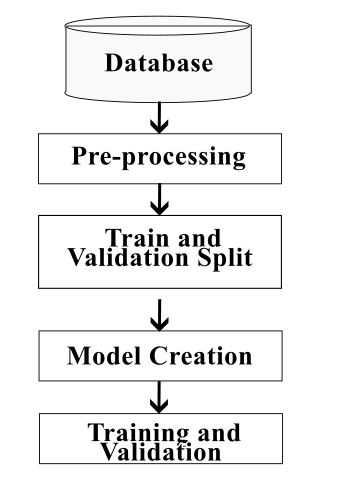
|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Reference No.** | **Method** | **Dataset** | **Performance Measures** | **Accuracy** | **Limitations** |
| [1] | Discovering the Best Feature Extraction and Selection Algorithms for Spontaneous Facial Expression Recognition | SIFT+FAP, mRMR, Adaboost and SVM | Feedtum and NVIE | Accuracy ± One standard deviation | Direct comparison of texture, geometry, and their fusion, in addition to numerous selection methods |
| [3] | Algorithm for Efficient Attendance Management: Face Recognition based  approach | Face  Recognition based approach, methods (Histogram  normalization, median filtering, Voila and Jones, Haar classifiers, Kernel Methods, Neural Networks, EigenFace) | own images from database | Accuracy | To increase the efficiency of face recognition algorithm using fast face detection algorithm. Limitation: There is a need to use some algorithms that can recognize the faces in veil to improve the system performance. |
| [2] | Direct comparison of texture, geometry, and their fusion, in addition to numerous selection methods | Adaboost, Detector Cascade | Original Dataset | Accuracy | Achieve high detection rate in processing images extremely rapidly. |
| [4] | Real Time Human Face Detection And Tracking | Vila Jones algorithm, Adaboost, Cascading | Own dataset | Accuracy | Real time human face detection and tracking |
| [5] | Convolutional Neural Networks (CNNs) for face mask detection and recognition. | Own Dataset - of over 500 images with masks and without masks | Accuracy | Exact value not mentioned | its sensitivity to different lighting conditions, camera angles |
| [6] | CNN, Mobile\_NetV2, Tensorflow framework | Own local dataset, separate test dataset | Accuracy | 96.85 | Small or imbalanced dataset, focused on evaluating the performance in controlled environments, not scalable |
| [7] | KNN, python libraries like bumpy, PIL, Keras OpenFace, Nvidia Software Development Kit. | Own dataset with photos of 11 student faces with 15 images to train and 5 images to test for each student | Accuracy | 100% for the dataset they created | It was not tested on a real life dataset which can lead to decrease in accuracy. It doesn't work well for faces with masks. |
| [8] | Unsupervised learning approach, GAN to generate synthetic face images, CNN for detection, ResNet | One normal  light face detection dataset WIDER FACE and the  low-light face detection dataset DARK FACE | Accuracy | 60.7% | Proposed HLA still requires many low-light  Images, extend HLA  to other high-level tasks |
| [9] | CNN with multiple convolutional & pooling layers, fully connected layers, FaceNet and OpenFace architectures, TensorFlow and Keras libraries | LFW and Pin Faces as network learning datasets,  ORL Faces dataset for testing | Accuracy, Precision, Recall | 98% | Privacy concerns, ethical implications |
| [10] | RCNN, YOLO V3, Azure | Own dataset with 20 photos of each student | Accuracy | 100% but only in paper’s dataset | The model is not tested for a large number of people. |
| [11] | Deep learning: Convolutional Neural Network, Spatial transformer network (STN) | Two datasets: LFW (Labelled Faces in the Wild) dataset, and their own classroom dataset | Accuracy | For LFW: 98.67%  For Classroom dataset: 100% | Limited training data (classroom data having only 25 frames) |
| [12] | Single shot multi-box detector and VGG network | Own dataset and WIDER dataset | Accuracy | 94.66% | Wider set of use cases won't work so advancement needs to be made in hardware for efficiency, powerfulness, |
| [13] | Face recognition system that uses OpenCV and deep learning techniques | Own dataset of real and fake faces. | Accuracy | authors report that the system achieves high accuracy | the privacy implications of collecting and storing facial images also need to be considered |
| [14] | Haar Cascade classifier with their proposed system | Own Dataset - Face video of 3–5 s recorded for every student in the class | Accuracy | 93.1% | Intolerant to noise, Proper security measures against attacks |

The majority of the works discussed above have restrictions regarding the amount of data available for training purposes, it has been observed. Either the dataset was small or the proposed models were not validated on real-world data, which may undoubtedly lead to a decline in the proposed system's performance and accuracy. Furthermore, it was observed that none of the works provided face detection and recognition for various situations, such as side views, faces with or without spectacles, etc. We have suggested employing transfer learning as a solution to these issues. ResNet50 serves as the foundation for our model, on top of which we build our layers.

1. **Proposed Model**

We outline our proposed framework architecture for automatic attendance, in which we want to feature extract after pre-processing the input photographs, and then compare with already-existing images in the database to mark attendance. We employ transfer learning, a deep learning and machine learning technique that uses a previously trained model as a starting point for a different but related job. Transfer learning is fine-tuning a pre-trained model that has already learned to recognise specific features on a new dataset or task as opposed to building a model from start on a big dataset. Here, our pre-trained model is ResNet50. It is a design for a deep convolutional neural network, which is frequently used in computer vision tasks like object and picture detection. It uses skip connections, also known as residual connections, to solve the vanishing gradient problem that can arise in very deep neural networks. It has 50 layers. On numerous benchmarks, this architecture has attained cutting-edge performance, and thanks to its success, ResNet has been developed in even more in-depth iterations. To ensure that our model does not overfit or underfit, we add a few additional layers and dropouts in addition to ResNet50.

Our objective is to identify every face in the frame and concentrate on it individually. Even if a face is turned in a different direction or is present in poor lighting, features must be taken into account in order to identify it. The model should also be able to identify distinctive facial characteristics, such as the size of the eyes or the length of the face, that can be used to identify one individual from another. In order to ascertain the person's name, these extracted features will next be matched to the features of known people. Fig. 1 below shows how these steps should be completed in order.



**Fig 1. Block diagram of proposed model**

**3.1 Database:** We have used the AT&T and FaceScrub database, which are openly accessible database with different images of distinct subjects taken at different time with varying lighting, facial expressions.

**3.2 Preprocessing:** After importing the dataset, we are resizing the images to 180\*180 and changed the extension (.pgm to .png).

**3.3 Train and Validation Split:** The pre-processed data is now divided into train and validation sets, we split the dataset into 80-20.

**3.4 Model Creation:** ResNet-50, a convolutional neural network with 50 layers, is what we employ. A network that has been pretrained using more than a million photos from the ImageNet database was loaded. Then, we supplemented the pretrained model with our own layers.

**3.5 Training and Validation:** After creating the model, we are running multiple epochs. Each epoch consists of training the model and validating it.

**4. Experimental Results and Analysis**

**4.1 Dataset**

**4.1.1 AT&T**

The dataset was obtained from kaggle and used in the context of a face recognition experiment conducted in collaboration with the Speech, Vision, and Robotics Group of the Engineering Department at Cambridge University.

Ten images are assigned to each of the forty distinct topics. There are pictures of people taken at different times of day, in different lighting, with the subject wearing or without wearing glasses, and with the subject's eyes open and a grin on their face. All the shots were taken head-on, with the subjects against a completely black background (though we did allow for some tilting and panning).

Each picture is 92 pixels by 112 pixels and has 256 shades of grey. There are a total of 40 individual folders containing the photographs; their names take the pattern sX, where X is the topic number (1–40). There are ten distinct pictures of that topic in each of these folders; their names have the form Y.pgm, where Y is the number of that picture (1–10).

Using the dataset presented some difficulties due to the fact that our photos are of the.pgm format and the keras library only accepts images with the.img,.png,.jpeg,.jpeg, etc. extension during preprocessing. The photos were changed to PNG format in this instance.

|  |  |
| --- | --- |
|  | **Classes (1 to 40)** |
| Number of images | 10 |
| Size of each image | 10.32 kB |
| Challenges | The images are available in .pmg format which is not accepted by keras library. |
| Sample |  |

**4.1.2 FaceScrub**

To facilitate studies in facial recognition and computer vision, the FaceScrub dataset was made available to the public. About 43,000 photos of famous people were culled from the internet and compiled by academics at Columbia University and the University of Massachusetts, Amherst.

The file includes pictures of the celebrity along with their name labelled. Male and female celebrities of all races and ethnicities are included in the collection, with photos taken in a broad variety of settings and poses.

Each image weighs in at between 3KB and 100KB in size. Each celebrity's photos are kept in their own individual folders. Each of these folders contains a different number of photos, each of which is named after the relevant celebrity and assigned a unique number. All of the pictures are around 100 pixels on the widest side and are available in JPEG, PNG, and BMP formats.

The vast volume of data in the FaceScrub dataset necessitates intensive processing resources, which proved to be one of the key obstacles researchers faced when working with the dataset. Due to the large scale and high dimensionality of the pictures, training deep learning models or performing complicated analysis may be computationally costly, calling for specialised hardware and rigorous optimisation tactics.

|  |  |
| --- | --- |
|  | **Classes (Name of Celebrities)** |
| Number of images | Varies between 40-200 |
| Size of each image | 3KB – 100KB |
| Challenges | The size of the dataset is large and require high computational power. |
| Sample | Sample images |

**4.2 Performance Metrics**

**4.2.1 Accuracy**

A value's accuracy is defined by how closely it corresponds to the expected or real value when measured or computed. It is frequently used in machine learning, data analysis, and other domains to evaluate the efficacy of models or algorithms and is typically stated as a percentage.

In binary classification problems, accuracy can be expressed in terms of the numbers of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), as follows:

where,

True positives (TP) - the cases where the model correctly predicts the positive class

False positives (FP) - the cases where the model predicts the positive class but the actual class is negative

True negatives (TN) - the cases where the model correctly predicts the negative class

False negatives (FN) - the cases where the model predicts the negative class but the actual class is positive

The range of accuracy as a metric is from 0 to 1.

An accuracy of 0 indicates that the model is not able to correctly classify any of the cases.

An accuracy of 1 indicates that the model is able to correctly classify all the cases.

**4.2.2 Validation Accuracy**

Machine learning models may be evaluated by how well they perform on a validation dataset that was not utilised during training. It is frequently employed to approximate the model's adaptability to novel, unseen data.

The validation set is used to check the model's accuracy and prevent overfitting while it is being trained during the machine learning process. The precision with which a model performs on the validation set is known as its validation accuracy.

The validation accuracy in binary classification problems can be expressed in terms of the numbers of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), as follows:

*Validation*

where,

True positives (TP) - the cases where the model correctly predicts the positive class

False positives (FP) - the cases where the model predicts the positive class but the actual class is negative

True negatives (TN) - the cases where the model correctly predicts the negative class

False negatives (FN) - the cases where the model predicts the negative class but the actual class is positive

Similar to accuracy, the range of validation accuracy as a metric is from 0 to 1.

A validation accuracy of 0 indicates that the model is not able to correctly classify any of the cases in the validation set.

A validation accuracy of 1 indicates that the model is able to correctly classify all the cases in the validation set.

**4.2.3 Loss**

Loss refers to the difference between the predicted values of the model and the actual values of the training data. It is a measure of how well the model is able to fit the training data.

The loss function that we used for our model is “Sparse\_categorical\_crossentropy”. It is a loss function used in machine learning for multi-class classification problems. It is similar to the “categorical\_crossentropy” loss function, but it is used when the class labels are integers instead of one-hot encoded vectors.

The mathematical formula for sparse\_categorical\_crossentropy loss function is:

where,

N: number of samples in the training data

y: actual class label of the training data (as integers)

y\_pred: predicted probability distribution over the classes by the model

Σ: summation operator

The range of the “sparse\_categorical\_crossentropy” loss function is from 0 to infinity.

0 indicates perfect predictions and higher values indicate worse predictions.

**4.2.4 Validation Loss**

A model's ability to generalise to novel, unknown data is quantified by its validation loss. A subset of the available data is often reserved as a validation dataset throughout the training phase. The validation loss is the value obtained by applying a loss function such as "sparse\_categorical\_crossentropy" to the model's performance on the validation dataset at the end of each training period.

The mathematical formula for the validation loss is the same as the loss function used during training, such as sparse\_categorical\_crossentropy. However, instead of evaluating the loss on the training data, the loss is calculated on the validation data.

where,

N: number of samples in the training data

y: actual class label of the training data (as integers)

y\_pred: predicted probability distribution over the classes by the model

Σ: summation operator

The range of validation loss is the same as the loss function, from 0 to infinity.

0 indicates perfect predictions and higher values indicate worse predictions.

|  |  |
| --- | --- |
| **Performance Metrics** | **Acceptable Range** |
| Accuracy | 0-1 |
| Loss | 0- |
| Validation Accuracy | 0-1 |
| Validation Loss | 0- |

**5. Result**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Method** | **Dataset** | **Accuracy** | **Loss** | **Validation Accuracy** | **Validation Loss** |
| ResNet-50 + 3 additional layers | AT&T | 1.00 | 0.0405 | 0.9872 | 0.2188 |
| FaceScrub |  |  |  |  |

Our model's accuracy is 1 as seen in the above table. We also have a test set and a validation set within our dataset. In order to ensure our model is generalizable, we use data that was not used during training, which can be found in the validation set. The result of our validation was a 98.72% success rate.

**6. Comparison**

**6.1 Dataset – AT&T**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Reference No.** | **Proposed Model** | **Existing Work** | **Proposed Model Accuracy** | **Existing Work Accuracy** |
| [15] | ResNet-50 + 3 additional layers | ANN combined with modified MAML. | 98.72% | 96.20% |
| [16] | ResNet-50 + 3 additional layers | Residual CNN - Resnet 152v2 is the residual network variation used by the authors | 98.72% | 97% |
| [17] | ResNet-50 + 3 additional layers | CNN with the Approximation Wavelet Transformation | 98.72% | 97.42% |
| [18] | ResNet-50 + 3 additional layers | AlexNet-CNN architecture-based transfer learning framework | 98.72% | fc6: 96%  fc7: 98.17%  fc8: 97% |
| [19] | ResNet-50 + 3 additional layers | AB-FR model, a convolutional neural network face recognition method based on BiLSTM and attention mechanism. | 98.72% | 96.79% |

**7. Conclusion**

In conclusion, the article proves that a transfer learning setup based on the ResNet-50 architecture with three extra layers can successfully complete a given job. The model was able to learn characteristics that were pertinent to the new dataset by drawing from the pre-trained ResNet-50 model on a big dataset. By including an additional three layers, the model was better able to adapt to the new challenge, leading to improved validation accuracy in comparison to previous works in the same field.

Our suggested method makes use of many facets of picture classification, object recognition, and segmentation, and the high accuracy it achieves has the potential to boost the effectiveness and precision of automated systems across a wide range of fields, including the automation of classroom attendance.

Overall, this research shows how transfer learning with pre-trained models, and the ResNet-50 architecture in particular, may help deep learning models do better on a variety of tasks. Our model may be fine-tuned for use with real-world data in a production setting with more study.

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