Noticing the Missing Child Using Machine Learning with Resnet 50 and VGG 16

Sai Greeshma Sree Pagidimarri[1], Velisala Madhu Babu[2], Komma Sanjay Bhargav[3], Gogula Vijay Kumar[4]
[1,2,3]*Department of CSE, CMR Technical Campus, Telangana, India*
[4]*Assistant Professor, Department of CSE, CMR Technical Campus, Telangana, India*

Abstract: Consistently, countless youths are accounted for missing in India. In cases of missing children, a significant number of children remain unidentified. A clever deep learning strategy for recognizing a detailed missing child from accessible pictures of an enormous number of youngsters utilizing facial acknowledgment is portrayed in this work. A shared webpage can have landmarks, comments, and photos of questionable children added by the public. The image will be instantly compared to the repository's registered images of the missing child. The youngster's image is sorted, and the photograph from the data set of missing kids with the best match is picked. Using the public-provided face image, a deep learning model is prepared to precisely distinguish the missing child from the missing child picture information base. For face identification, the Convolutional Neural Network (CNN), a powerful deep learning method for picture-based applications, is utilized. Face descriptors are extracted from images using a pre-arranged CNN model VGG-Face significant plan. Our strategy, rather than different utilizations of deep learning, just utilizes a convolution network as an undeniable level component extractor, with a prepared SVM classifier taking care of youngster location. A deep learning model that is heartless toward commotion, enlightenment, contrast, impediment, picture posture, and youngster age is made by appropriately preparing the best face acknowledgment CNN model, VGG-Face. This model outperforms previous face recognition-based methods for identifying missing children. The kid identification system has a classification accuracy of 99.41%. 43 kids participated in the testing.

Keywords: Face recognition, missing child identification, deep learning, CNN, VGG-Face, and multi-class SVM.

1.INTRODUCTION

A nation's most valuable asset is its children. Every nation's future depends on the education of its youth. Children make up a critical piece of India's populace, making it the world's second-most crowded country. Nonetheless, countless children vanish every year in India for different reasons, including seizing, snatching, dealing, and lost kids. Despite the fact that there are 174 missing kids in India on a normal day, a big part of them can't be found, which is a genuinely disturbing truth. Children who vanish could be exploited and abused for a variety of reasons. A report from the National Crime Records Bureau (NCRB) that was mentioned in Parliament by the Ministry of Home Affairs (MHA) (LS Q no. 3928, 20.03.2018) Prior to 2016, more than one lakh children (really 1,11,569) were reported missing, and 55,625 were still missing at the end of the year. The number of missing children, according to numerous nongovernmental organizations, is significantly higher than previously thought.

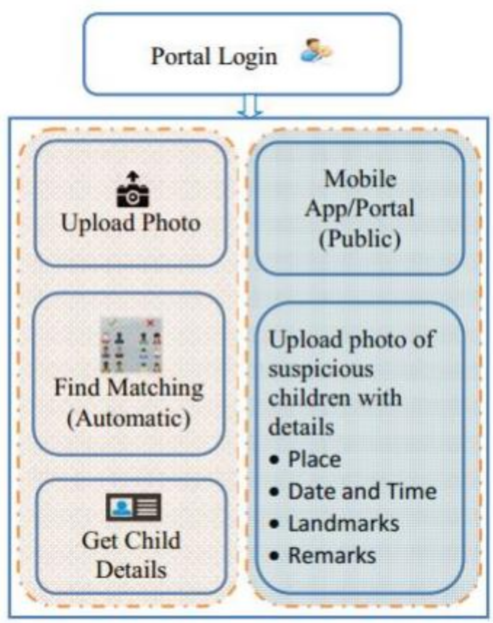

Fig.1 Children identification system

Most cases including missing kids are accounted for to the specialists. A lost child may be located in another state or location for a variety of reasons. Even if a child is found, it is difficult to identify them among the detailed cases of missing children. A structure and design strategies for a child-recovery aid are described in this study. A concept for the preservation of a virtual environment is presented, in which current images of missing children that are supplied by parents are stored in a repository. It is encouraged for members of the public to upload images of children in suspicious settings to the internet. An automatic search for this image among case photos of missing children will be included in the program. This makes it more straightforward for cops to find the child anyplace in India.

2.LITERATURE REVIEW

Face recognition using histograms of oriented gradients

Face recognizable proof has for quite some time been an issue in PC vision. Recently, it was demonstrated that histograms of oriented gradients (HOGs) are an excellent description for face recognition and object identification in general. In this examination, we explore a direct yet productive technique for utilizing HOG highlights for face acknowledgment. Three significant commitments are made in this paper: To begin, we propose eliminating HOG descriptors from a standard network in order to address obstacles, stance, and lighting-related flaws in face highlight identification. Second, the acquisition of essential structure for face identification is made possible by combining HOG descriptors at various scales. Thirdly, we demonstrate the significance of dimensionality reduction in reducing overfitting and noise in the classification process. This is especially important for getting HOG features out of cells that overlap. Finally, the benefits of our method are demonstrated by data from four databases.

Face recognition using sift features

The SIFT (Scale Invariant Feature Transform) method has proven to be effective for general object detection and recognition. In this paper, we present two novel approaches to face identification that are based on the original SIFT method: Partial-Descriptor-SIFT (PDSIFT) and Volume-SIFT (VSIFT) We contrast feature-based methods like SIFT and PDSIFT with holistic methods like Fisherface (FLDA), NLDA, and Eigenfeature Regularization and Extraction (ERE). PDSIFT outperforms the original SIFT technique significantly, as demonstrated by experiments on the ORL and AR datasets. In addition, PDSIFT significantly outperforms FLDA and NLDA and may perform similarly to the most successful holistic technique, ERE.

MISSING CHILD IDENTIFICATION USING FACE RECOGNITION SYSTEM

Because it conveys individuals' identities, the human face is essential for social interaction. Face recognition is a skill that most people use on a daily basis. One of the most significant biometric advancements, face acknowledgment, has filled in significance because of fast headways in computerized cameras, the Web, and cell phones, as well as developing security prerequisites. A face acknowledgment framework is a piece of programming that utilizes a computerized picture or a video outline from a video source to recognize or confirm an individual. A PC based computerized innovation known as the Face Acknowledgment Framework is the subject of flow research. This review examines the development of a face acknowledgment framework employing the Principal Component Analysis (PCA) method. Most of the time, face acknowledgment calculations combine the PCA. It decreases the dimensionality of the picture, yet it in like manner keeps a part of the image data instabilities. Projecting a face picture into an element space that incorporates the huge qualifications between realized face pictures is the means by which the strategy works. Since they address the eigenvectors, or Head Parts, of the assortment of appearances, the significant qualities are alluded to as "Eigen faces." be that as it may, they don't necessarily match to highlights like eyes, ears, and noses. Recognizing a particular face simply requires comparing these weights to those people because the projection operation defines each face as a weighted sum of the Eigen face characteristics.

VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION

In this paper, we investigate the relationship between a convolutional network's profundity and its overall scale picture recognition accuracy. Utilizing a design with tiny (3 x 3) convolution channels, we direct a far reaching investigation of organizations of expanding profundity. This shows that rising the significance to 16-19 weight layers could achieve a basic improvement over existing game plans. This is our primary commitment. Our ImageNet Challenge 2014 proposition depended on these revelations, and it won first and second places in the confinement and characterization classifications, separately. What's more, we accomplish state of the art results by showing how well our portrayals adjust to different datasets. To encourage further research into the use of deep visual portrayals in PC vision, we have made our two most effective ConvNet models available to the general public.

Deep Face Recognition: A Survey:
To produce data representations with varying degrees of feature extraction, deep learning makes use of numerous processing layers. The study landscape of face recognition (FR) has been altered by this emerging technology since the 2014 breakthroughs of DeepFace and DeepID. Because of its progressive plan for sewing together pixels into an invariant face portrayal, profound learning has since altogether worked on current execution and advanced fruitful certifiable applications. In this review, we give a complete examination of the latest advances in profound FR, covering many subjects like calculation plans, data sets, conventions, and application situations. We begin by providing a synopsis of the various loss functions and network designs that have been presented as part of the rapid advancement of deep FR methods. Second, there are two categories of face processing techniques: one-to-numerous increase" and "many-to-one standardization." Then, we sum up and analyze the datasets that are commonly utilized for model preparation and appraisal. Third, we investigate cross-factor, heterogeneous, multiple-media, and industrial scenes as deep FR contexts. In conclusion, numerous intriguing routes and technological issues are discussed.

MatConvNet Convolutional Neural Networks for MATLAB:
MatConvNet is a MATLAB execution of Convolutional Neural Networks (CNNs). The tool stash was planned in light of simplicity and flexibility. It gives simple to-involve MATLAB capabilities for working out straight convolutions with channel banks, highlight pooling, and other principal CNN parts. MatConvNet empowers the preparation of mind boggling models on huge datasets like ImageNet ILSVRC by considering the fast improvement of novel CNN structures while keeping up with help for proficient computer processor and GPU figuring. This article explains MatConvNet's implementation of CNNs and the technical details of each computational block in the toolbox.

3. IMPLEMENTATION

The specialists have an answer for the majority of cases, including those involving missing children. A lost child may be located in another state or location for a variety of reasons. Regardless of whether a child is found or not, it is difficult to identify them from the reported missing cases. A structure and design strategies for a child-recovery aid are described in this study. A concept for the preservation of a virtual environment is presented, in which current images of missing children that are supplied by parents are stored in a repository.

Disadvantages:

- PC vision highlights like Hoard, LBP, Filter, and SURF were vigorously used in early face recognizable proof strategies. In face acknowledgment, be that as it may, hand-exacerbated highlights than highlights removed utilizing a CNN organization.

A clever deep learning strategy for distinguishing a revealed missing child from accessible pictures of an enormous number of youngsters utilizing facial acknowledgment is portrayed in this work. A shared webpage can have landmarks, comments, and photos of questionable children added by the public. The image will be instantly compared to the repository's registered images of the missing child. The youngster's image is ordered, and the photograph from the information base of missing children with the best match is picked. Using the public-provided face image, a deep learning model is prepared to precisely identify the missing child from the missing child picture data set. For the missing child project, understudies must use RESNET 50 and VGG 16 to compare their accuracy to CNN.

Advantage:

- Here, a deep learning engineering with these limitations is constructed.

- The proposed framework is very direct, sensibly estimated, and trustworthy in contrast with existing biometrics like iris and unique finger impression acknowledgment frameworks.
- Students want to use RESNET 50 and VGG 16 for the missing child project and compare their accuracy to CNN.

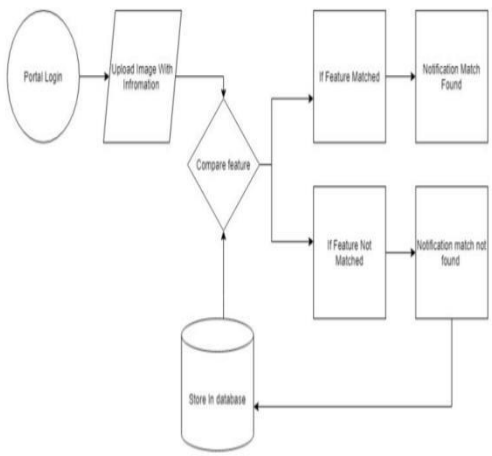

Fig.2: System architecture

At the point when a youngster is found, the photo taken at that point and the photos put together by the kid's watchman or the police at the hour of the vanishing are looked at. The child may have been missing for a considerable amount of time at times. Since aging alters the shape and texture of the skin, this age difference can be seen in the photos. A feature discriminator that is resistant to the effects of aging must be developed. This is the most difficult test in missing child distinguishing proof when contrasted with other facial acknowledgment frameworks. Adjustments in position, direction, lighting, impediments, foundation commotion, and different variables may likewise change the kid's look. Because of the way that it was gained from a distance without the kid's information, the public picture may not be of great. Here, we foster a deep learning [1] design that considers these limitations. The proposed framework is basic, savvy, and trustworthy in contrast with existing biometrics like iris and unique mark acknowledgment frameworks.

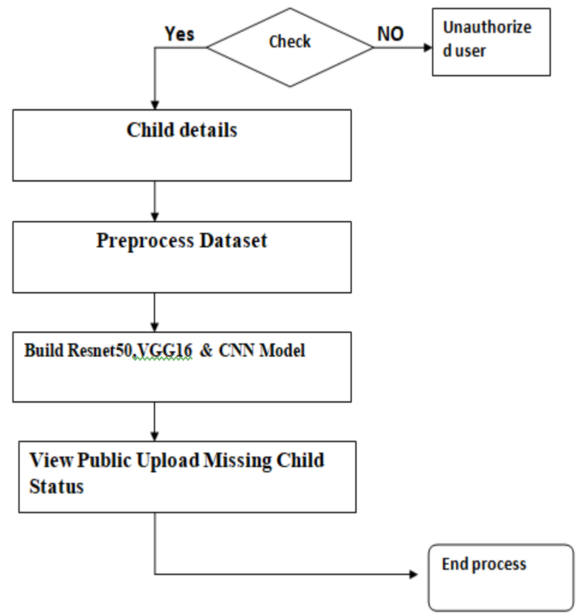

Fig.3: Dataflow diagram

MODULES:

- Admin
- User

A deep learning CNN expectation model is worked with the assistance of the public dataset of missing children from FGNET. At the point when a public transfers a thought youngster's photo, this model will really look at the prepared model to check whether the kid is in the missing data set after the model has been prepared. Official work force will actually want to get to this found outcome whenever thanks to its capacity in a data set.

In light old enough and other facial attributes, the SVM Multiclass classifier is utilized to separate face qualities from photographs. The distinguished face is then taken care of into the CNN model, which predicts whether this face exists in the picture data set.

Extension Module:

- RESNET 50 and VGG 16's accuracy should be compared to CNN's in the case of a missing child.
- The number of epochs increases the accuracy of all algorithms. In the graph above, RESNET is represented by the green line, VGG 16 by the blue line, and CNN accuracy by the orange line.
- CNN and VGG 16's accuracy has been improved.

4. ALGORITHMS

CONVOLUTIONAL NEURAL NETWORK:

A six-layer neural network that can recognize one picture from one more will be built to exhibit the development of a picture classifier in view of convolutional neural networks. We will develop a moderately little organization that can likewise be run on a central processor. On a standard CPU, training traditional neural networks that excel at picture classification takes a long time and has many more parameters. Nonetheless, we want to exhibit how to utilize TENSORFLOW to develop a genuine world convolutional brain organization.

Optimisation problems are addressed by mathematical models known as neural networks. Neural networks' fundamental computational units, neurons, are what make them up. A neuron receives data (such as x), performs computation on it (such as copying it by w and adding another variable b), and generates a result (such as z= wx+b). To create the neuron's last result (initiation), this worth is taken care of into a nonlinear capability called enactment capability (f). There are an assortment of enactment capabilities to browse. A significant enactment capability is the sigmoid. A sigmoid neuron is a neuron that involves the sigmoid capability as an initiation capability. A layer is the following structure block of brain organizations and is made by stacking neurons in a solitary line. The name of a neuron is determined by its activation function; there are many different types of neurons, including TanH and RELU. The image with layers appears below.

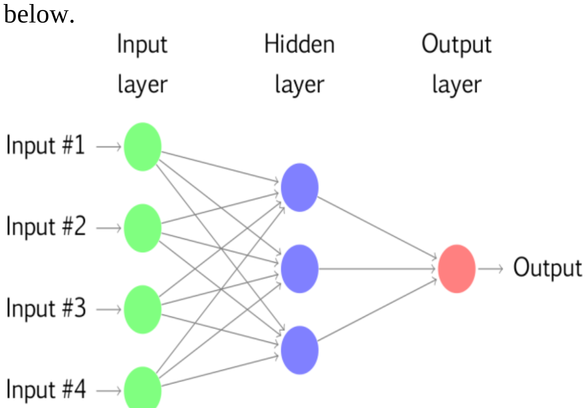

Fig.4: CNN layered architecture

In order to forecast picture class, a number of layers interact with one another to determine the layer with the best match. This process is repeated until no more improvements can be made.

VGG -16 ALGORITHMS:

Under the title "Very Deep Convolutional Networks for Large-Scale Image Recognition," K. Simonyan and A. Zisserman of the College of Oxford distributed the CNN model known as VGG16. In ImageNet, a dataset consisting of more than 14 million images divided into 1000 classes, the model has a best 5 test exactness of 92.7 percent. It was one of the well-known models that the ILSVRC-2014 accepted. By substituting massive channels with a bit size of 33 in succession in the first and second convolutional layers, which are 11 and 5, separately, it outflanks AlexNet. VGG16 had been using NVIDIA Titan Black GPUs for weeks for training.

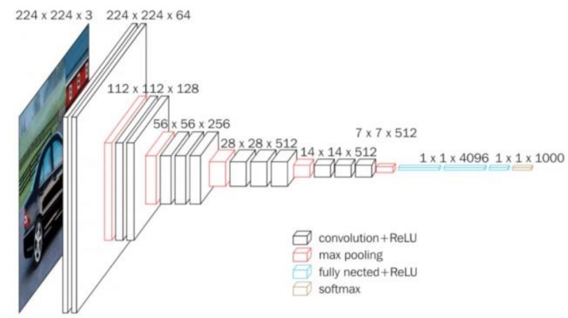

Fig.5: VGG16 model

RESNET-50:

Deep leftover organizations are made up of convolutional neural networks (CNNs) with 50 layers, like the well-known ResNet-50 model. A residual neural network (ResNet) is a type of artificial neural network (ANN) that constructs an organization by stacking leftover blocks on top of one another. You will learn everything you need to know about the remaining brain organizations and the most frequently used ResNets, such as ResNet-34, ResNet-50, and ResNet-101.

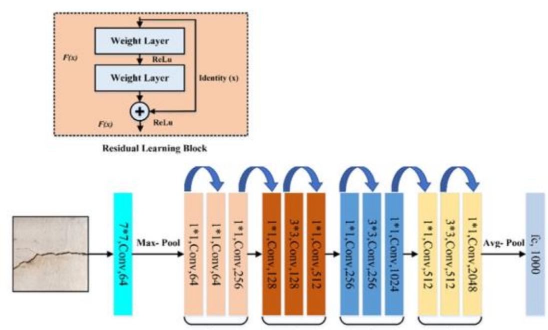

Fig.6: Resnet50 model

Almost all of the most recent AI technologies build cutting-edge systems using ResNets. ResNets work by building deeper networks than other simple networks and figuring out the best number of layers to avoid the vanishing gradient problem at the same time. ResNet-50 is a 50-layer deep CNN. A pretrained model of the company that was developed using more than one million images from the ImageNet database can be stacked [1]. The pretrained network can group pictures of consoles, mice, pencils, and other animals into one of 1,000 different thing categories.

5. EXPERIMENTAL RESULTS

Fig.7: Home screen

By clicking the link labeled "Public Upload Suspected Child" on the screen above, the general public can access the following page.

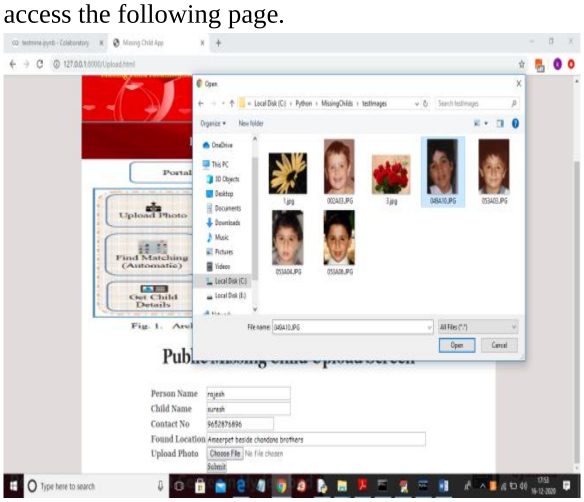

Fig.8: Public Upload Suspected Child

Upload the child that was found in the database on the preceding screen, and then click the "Official Login" link to access the login page that is displayed below.

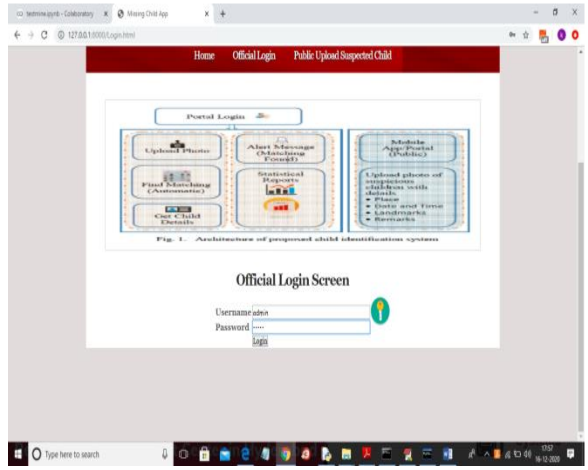

Fig.9: Official login

The administrator can use the username and password "admin" and "admin" to log in on the above page.

Fig.10: login

By clicking the "check Public Upload Missing Childs Status" link on the upper page, officials can view all uploads and their results.

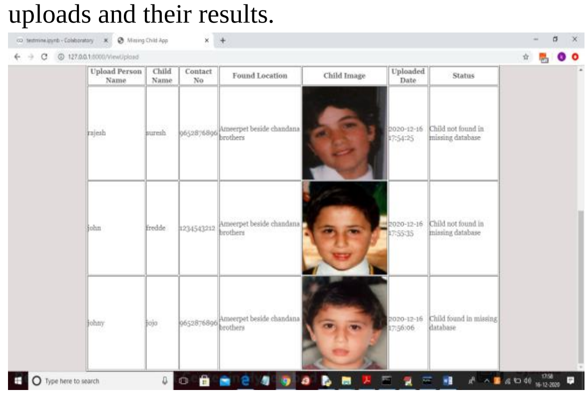

Fig.11: View Public Upload Missing Childs Status

Officials can look at all the information on the screen above and then act to find the child. A comparison graph between RESNET, VGG, and CNN can be seen while the code is running on the screen above, where we are performing transfer learning with RESNET. To view the comparison graph, sign in as OFFICIAL and then click the link labeled "Build Resnet 50, VGG 16 & CNN Model."

Fig.12: Build Resnet 50, VGG 16 & CNN Model

To obtain the graph displayed below, click the link labeled "Build Resnet 50, VGG 16, and CNN Model" on the same screen.

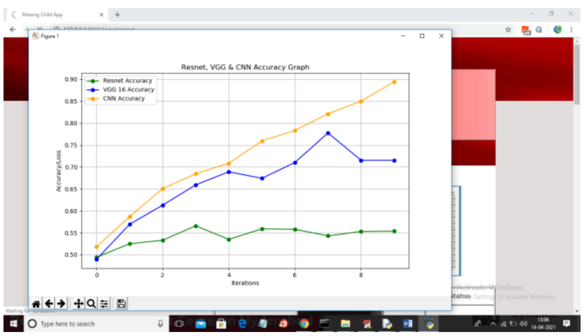

Fig.13: Graph

In the graph above, age/cycle is tended to by the x-center and precision by the y-center point. If everything is equal, precision decreases with age. The exactness of CNN is represented by the orange line, RESNET by the green line, and VGG 16 by the blue line.

Algorithm Name	Accuracy	Loss
Resnet 50	0.5538922	0.686696759954898
VGG 16	0.7153558	0.60162911775258
CNN	0.8942116	0.259194134416694 4

Fig.14: Table

Each method's final accuracy and loss value can be seen in the table above; for a better model, the algorithm's accuracy and loss must be high.

6. CONCLUSION

A missing child ID framework combines a strong CNN-based deep learning strategy for highlight extraction with a help vector machine classifier for ordering distinct child groups. This framework is tested using a prepared deep learning model that includes depictions of children's faces. Predominant execution was achieved by removing the softmax from the VGG-Face model and extracting CNN picture highlights to create a multi-class SVM. The presentation of the recommended framework is evaluated using images of children taken in a variety of lighting, sound, and ages. The grouping had a higher exactness of 99.41 percent, indicating that the proposed facial recognition technology could be used to precisely identify missing children. For the missing child project, understudies must use RESNET 50 and VGG 16 to compare their accuracy to CNN.

• For the missing child investigation, understudies must involve RESNET 50 and VGG 16 and compare their accuracy to CNN. The accuracy of all calculations improves with age. In the chart above, RESNET is represented by the green line, VGG 16 by the blue line, and CNN accuracy by the orange line.

7. FUTURE SCOPE

We really want to foster this procedure in the future by partner our structure to public cameras and using steady face disclosure. The public cameras will consistently send the edges to our framework, which will screen them ceaselessly. At the point when one of the casings uncovers a missing individual, the fitting specialists are reached.

8.ACKNOWLEDGEMENT

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