In-vehicle baby alert system

Advanced Digital Image Processing project

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date TBD

Introduction

Vehicular heatstroke is largely underestimated by the general public. The majority of parents are misinformed and likely to believe that they could **never forget** their child in a vehicle.

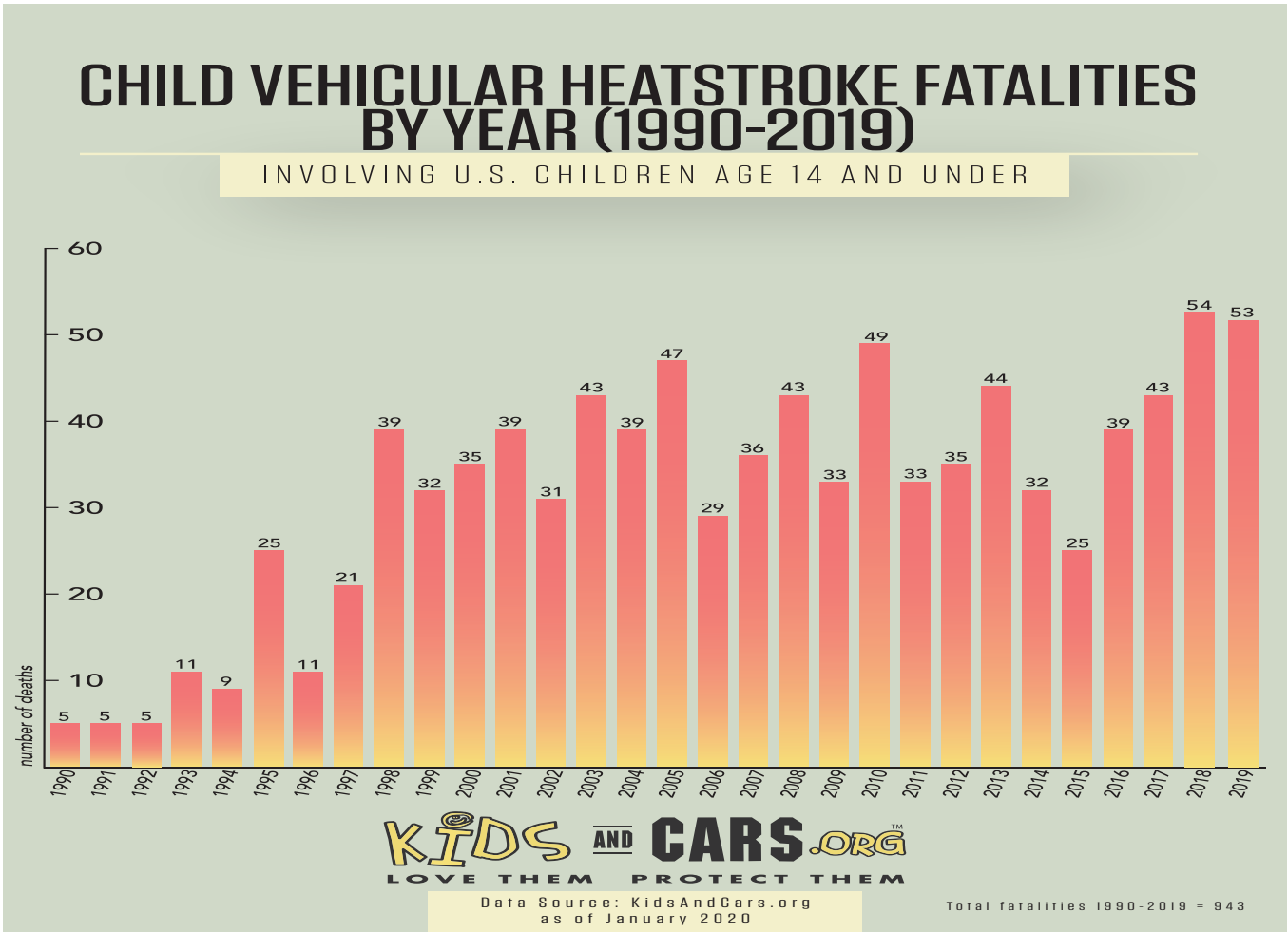
In over 55% of these cases, the person responsible for the child's death unknowingly left them in the vehicle. The most dangerous mistake one can make is to think leaving a child alone in a vehicle could never happen to them.

Introduction

The inside of a vehicle heats up very quickly! Even with the windows cracked, the temperature inside a car can reach **51 degrees Celsius** in minutes.

A child's body overheats three to five times faster compared to an adult, and heatstroke occurs when the body's temperature exceeds 40 degrees Celsius and the body organs begin to shut down.

Introduction: Some Data



Introduction: Project Proposal

Based on what we have learned about Computer Vision and Image Processing, a possible solution would be to design a new system which enables **adult/child's face detection**.
Even better, a hybrid solution which combines several way of measuring/sensing the child's presence would be more robust.

Our proposal is composed of three main steps:

- Collecting the data and building a dataset;
- Model selection and synthetic testing;
- Field testing of the best model.

The Dataset: Collecting The Data

This is the most challenging part of the project. Getting pictures of children under the age of 3 years old is not that easy.

In the beginning, we scraped images from Google Images, but we opted for a pre-existing licensed dataset[1].

[1] Eran Eidinger, Roee Enbar, and Tal Hassner. "Age and gender estimation of unfiltered faces". In: *IEEE Transactions on Information Forensics and Security* 9.12 (2014), pp. 2170–2179.

The Dataset: Sub-sampling And Dataset Adjustments

Since the pre-existing dataset is designed for a multi-class age classification task, we applied sub-sampling.

This yields an equal number of samples for adults and children, thus focusing the problem on a **binary classification task**.

Moreover, we decided that the images should mostly contain faces with as little background as possible. To this end, we fed our images into a face extractor[2].

[2] We settled for MTCNN over HAAR cascade.

Dataset - Definitive Version

Eventually, the dataset has been split in:

- Training set: 3520 child faces and 3624 adult faces
- Validation set: 379 child faces and 401 adult faces
- Test set: 387 child faces and 238 adult faces

Use-Case Overview

The classification task consists of 3 steps:

1. Image acquisition from a USB camera (e.g Logitech C270);
2. Face extraction with MTCNN;
3. Classification of the extracted faces.

Face extractor

As mentioned above, we used a face extractor for two reasons:

- Training set creation: labeling faces by hand was too slow and tedious
- Extraction of faces from the acquired image (main use case)

We began with HAAR cascade, both frontal and lateral, then switched to MTCNN, which proved far superior.

MTCNN

Framework:

- Image resizing for the creation of a piramid of images
- The image piramid is fed to three different CNNs:
  1. First, the **P-Net** produces a large number of candidate BBs[3] and performs BB regression, followed by NMS[4] for merging the overlapping ones.
  2. Surviving candidates are fed to the **R-net** that performs BB regression and again NMS.
  3. At last, the survived boxes are fed to the **Q-net** that performs similarly to the R-net but it is more complicated and outputs the positions of **five facial landmarks**.

[3] BB = Bounding box

[4] Non-maximum suppression

MTCNN

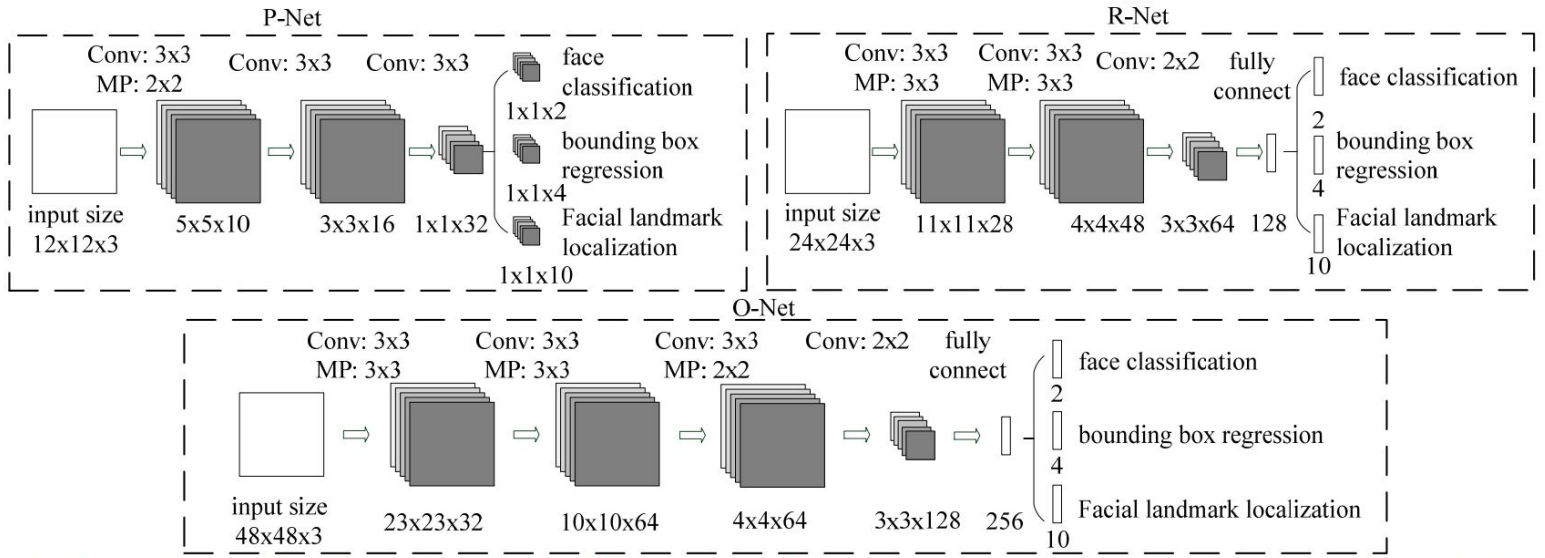


Fig. 2. The architectures of P-Net, R-Net, and O-Net, where "MP" means max pooling and "Conv" means convolution. The step size in convolution and pooling is 1 and 2, respectively.

Figure: MTCNN schematics[5].

[5] Kaipeng Zhang et al. "Joint face detection and alignment using multitask cascaded convolutional networks". In: *IEEE Signal Processing Letters* 23.10 (2016), pp. 1499–1503.

Fischerface - Generalities

TODO

Siamese Neural Network: Introduction

As previously mentioned, age classification is a challenging problem due to the complexity of the features that make up a face.

So we chose a **discriminative** approach, since we want to be able to separate **children** from **non-children**.

This was achieved by taking advantage of a **Siamese neural network**[6] that takes two inputs: a **template** image and the input image from the face extractor and checks if they belong to the same class or not.

[6] Actually there is only one network that is used to process the two inputs.

Siamese Neural Network - The Pairs

This kind of neural networks require in input a pair of images:

- Template image: the class example
- Input image: the image that has to be classified

The label $(1, 0)$ symbolizes that the template image and the input image belong to the same class, $(0, 1)$ otherwise.

Siamese Neural Network - The Pairs

We selected 26 child images as templates and paired them with all the other images in the original dataset[7], obtaining a new larger set of samples. The same procedure has been done with the adults images.

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Creating Datasets

Training set:
Number of same class image pairs = 95391, Number of different class image pairs = 97848, total sample pairs: 193239

Validation set:
Number of same class image pairs = 10584, Number of different class image pairs = 10827, total sample pairs: 21411

Test set:
Number of same class image pairs = 10800, Number of different class image pairs = 6426, total sample pairs: 17226
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Figure: Siamese training - validation - test set (children network)

[7] We excluded the pairs which contained the same image

Siamese Neural Network - General Architecture

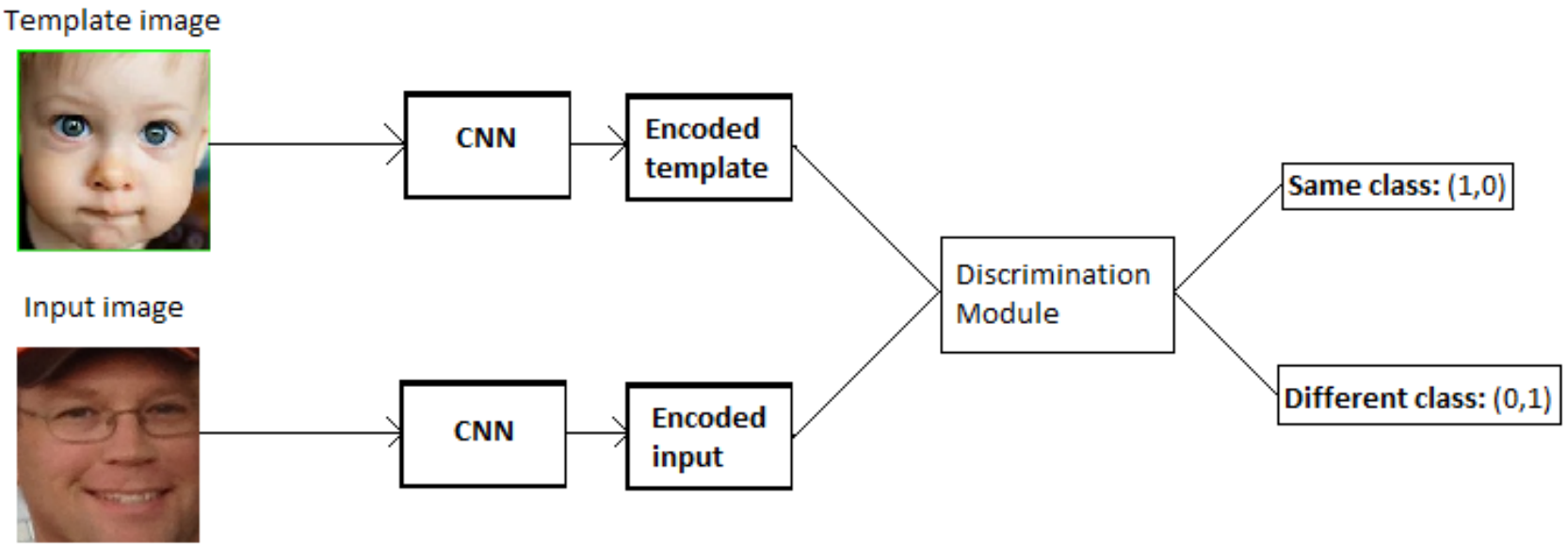

Figure: General outline of the network, the CNN is the same for both images

Siamese Neural Network - Discrimination module

The CNN part of the system actually works as an image encoder, extracting features from both the template and the input image [8], which are then fed to the **discrimination module**.
The paper[9] that inspired this approach used a joining neuron that calculated the cosine distance between the encoded vectors.
We decided to implement two different discriminator modules, one based on the **euclidean distance** between the CNN-encoded vectors and for the other one a **multi-layered perceptron** which was fed the concatenation of the two encoded vectors.

[8] Could be optimized at runtime by preprocessing the templates

[9] Jane Bromley et al. "Signature verification using a" siamese" time delay neural network". In: *Advances in neural information processing systems*. 1994, pp. 737–744.

Siamese Neural Network - Model selection strategies

We began our work by implementing a modified, slimmed-down version of the VGG16 architecture, based on the remarkable results that this model obtained in **ILSVRC**[10] 2014.

However, we were not satisfied with the results, so we decided to build a custom network and started the cross-validation process. This however was taking too long even for a small subset of hyperparameters (although it was giving very decent results when we stopped it, see table below).

So we devised a very simple evolutionary algorithm, with accuracy on validation set as fitness function.

[10] ImageNet Large Scale Visual Recognition Competition

Fisherface - Training results

TODO

Siamese Neural Network - Training results

We tested the resulting networks on the appropriately[11] held-out test set and obtained[12]

Model	Accuracy	Loss
VGG16 + MLP (Adults)	90.43%	0.5991 (H)
VGG16 + MLP (Child)	90.24%	0.5986 (H)
CV (Child)	93.06%	0.5751 (H)
Evo (Child)	**94.07%**	**0.5628** (H)
Evo (Adults)	**93.46%**	**0.5658** (H)

[11] Two different sets, one for adults and one for children

[12] H = Hinge loss

Siamese Neural Network - Selected architectures

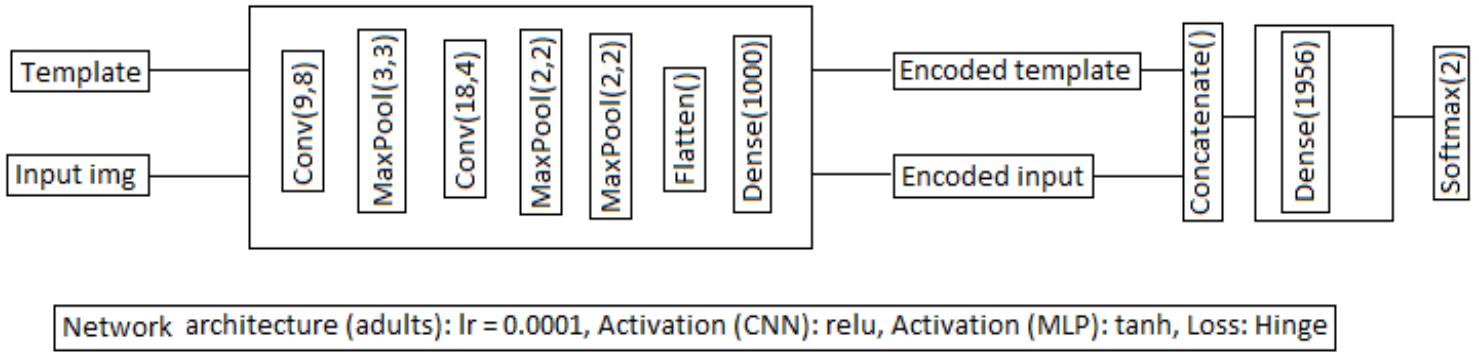

Figure: Selected architectures, Optimizer (both): Nadam

Autoencoder

TO BE DETERMINED

SIFT-SURF trade-off

TODO trade-off tra dimensione del set di indicatori e velocità di esecuzione

RGB vs BGR in OpenCV

TODO

Min face dimension for MTCNN

TODO

Thank You.