Table 2: Datasets used for training for each risk situation

Risk situation	Positive samples	Negative samples
Risk of domestic accident	406	600
Risk of fraud	120	180

4 EXPERIMENTS AND RESULTS

4.1 Visual Dataset

Thus we conducted experiments to recognize two risk situations on the visual part of LSC dataset [27]. It comprises 41664 images. We have selected four semantic risk classes, but have conducted experiments only on more semantic classes "risk of fraud" and "risk of domestic accident" 3. To avoid too similar images, we have limited our selection of images from the LSC dataset to one image per minute, which reduces the total number of images to 21,152. The classification problem we solved was binary. The positive example images in original LSC dataset for these two semantic risk situations are not numerous. The negative examples were selected proportionally. The figures are presented in Table 2. The constitution of these two datasets was done by taking the positive samples of a class and by randomly selecting ×1.5 images of the number of positives from the rest of the dataset.

For data augmentation, rotations, vertical and horizontal flips, left and right image translations and Gaussian noise addition were performed.

Finally, for the risk of a domestic accident, the training dataset consisted of 4224 images, 201 images for validation and 101 for testing. For the risk of fraud, the training dataset consists of 1254 images, 60 images for validation and 31 for testing.

4.2 Results of detection of two semantic risk situations

The Alexnet model [31] presented in the section was used as a classifier 3.

We proceed with the analysis of the Alexnet model training curves for the two risk situations and illustrate them in figure 1 and figure 2, noting that the hyperparameters of the AlexNet model have been optimized for each of the risk situations separately, see section 3. As illustrated in figure 1, for the risk of domestic accidents we obtain rather good results and the model does not overfit on the whole training dataset, we get an accuracy of 81, 33% on the test set rather quickly at epoch 14. For the risk of fraud, good accuracy is obtained of 96, 88% on the test set at epoch 22, see figure 2 after this time, the overfitting is observed and validation loss diverges.

5 CONCLUSION AND PERSPECTIVES

This research is the first attempt to use deep CNN framework for semantic risk situations detection with visual content on a lifeLog data. We have tackled a complex problem of recognition of semantic risks situation in the daily lives of fragile people. Thus the definition of matching of general concepts to risk concepts was an important part of the work. We have used a well-known model Alexnet with the stochastic gradient descent (SGD) with Nesterov momentum,

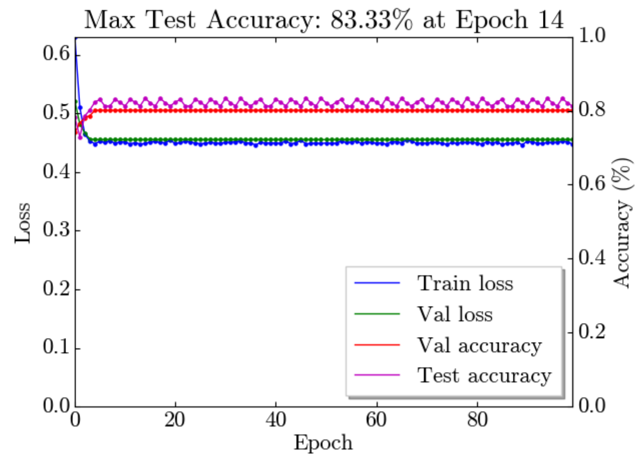

Figure 1: Alexnet curves for risk of domestic accident. The maximum accuracy (83, 33%) is attained at epoch 14

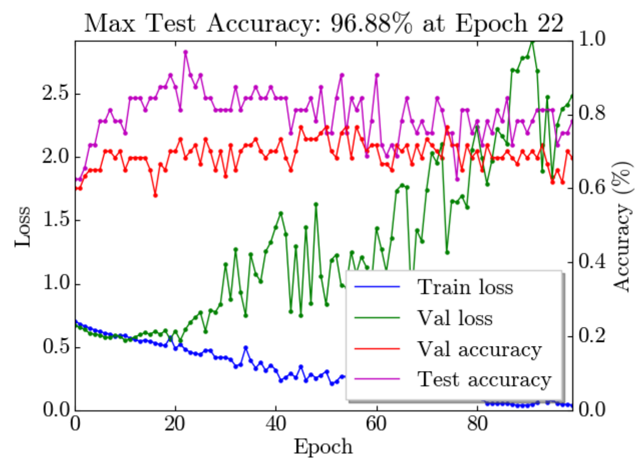

Figure 2: Alexnet curves for risk of fraud. The maximum accuracy (96, 88%) is attained at epoch 22

but have thoroughly tunned parameters. The results are promising, and in perspective, we will combine the developed strategy with multi-sensory data on fragile subjects.

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