11th International Symposium on Intelligent Distributed Computing, Belgrade, Serbia, October 11-13, 2017

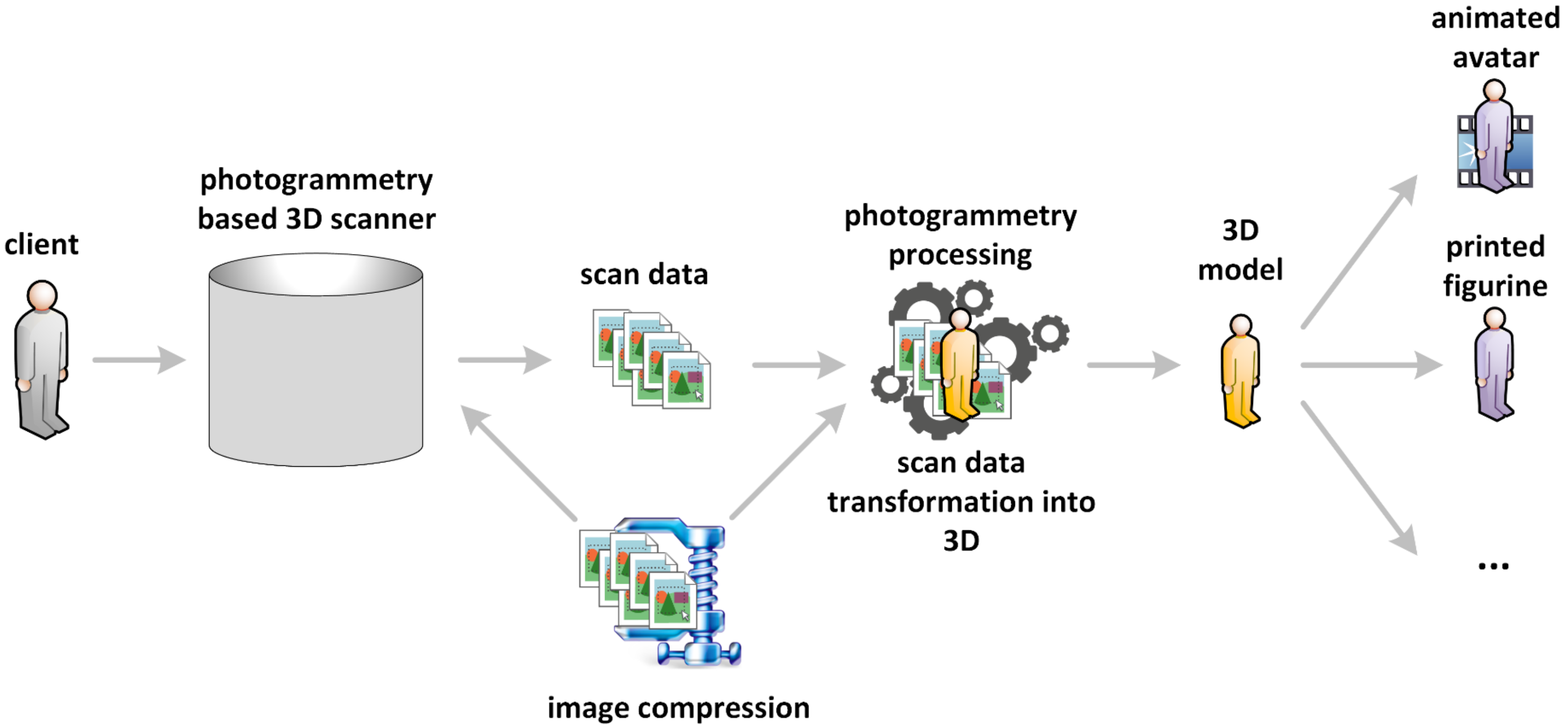
Binary Classification of Images for Applications in Intelligent 3D Scanning

Branislav Vezilić, Dušan Gajić, Dinu Dragan, Veljko Petrović, Srđan Mihić, Zoran Anišić, Vladimir Puhalac

Outline

Introduction

- 3D scanning process



Introduction

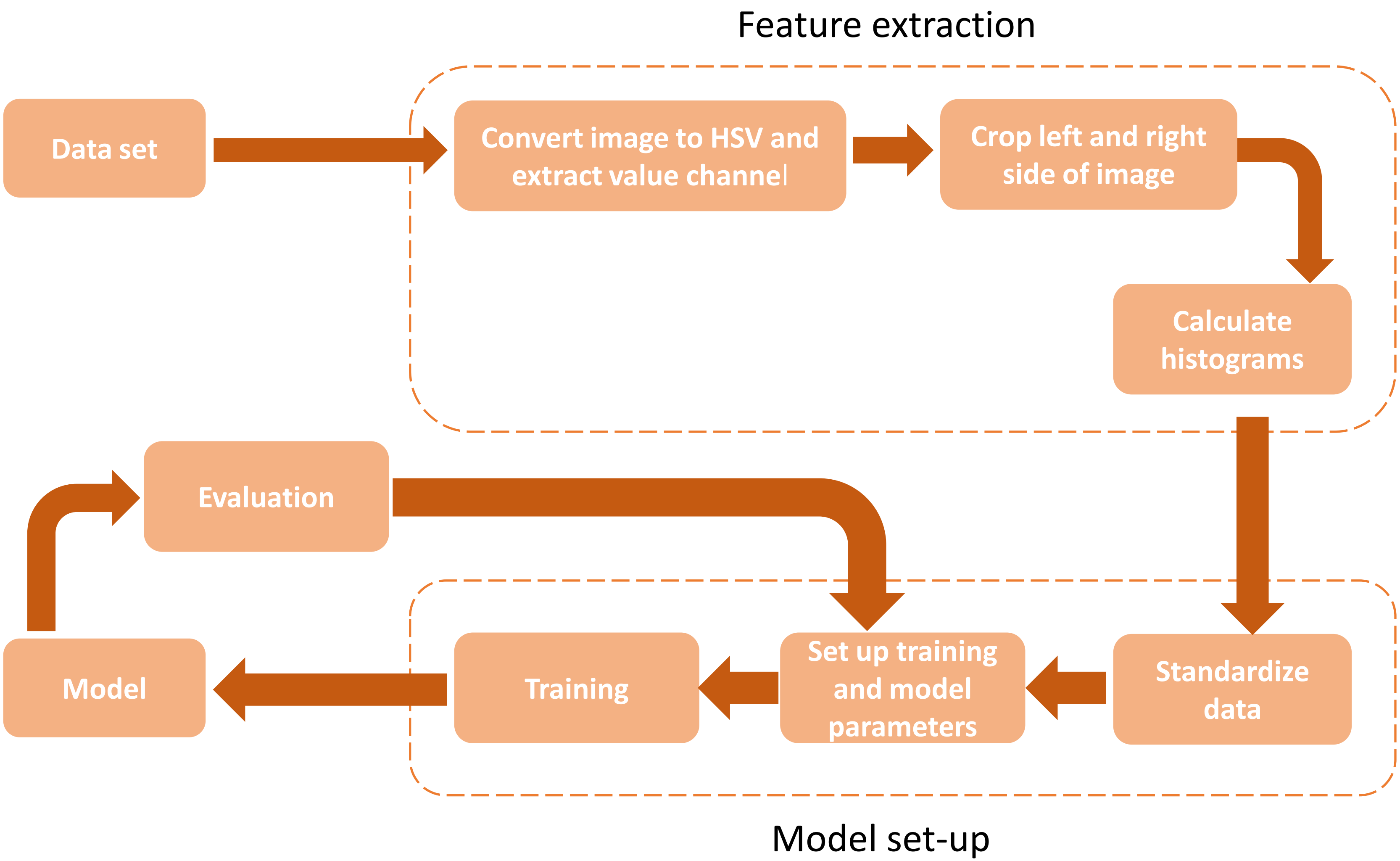
MISFIRED IMAGE

NORMAL IMAGE

Introduction

- Our goal is to create a system that is able to detect images with darker areas
- We differentiate two classes:
  - Normal images
  - Misfired images (as we like to call them)
- Our approach:
  - Manually extract features from images
  - Use them as input to selected machine learning algorithms

Overview of the Research Approach



Data Set

- Data set consists of 26,027 images with resolution of 5184 x 3456 in JPEG format
- All images are resized to resolution 400 x 266
- Only 2,729 out of 26,027 images (10.49%) are marked as misfired
- Balanced data set is produced by randomly sampling normal images from remaining data
- Balanced data set = equal number of samples per class
- Additional manual removal of outliers
- **FINAL SET:** 2,589 images spread across both classes

Feature Extraction

Convert image to HSV and extract value channel → **Crop left and right side of image** → **Calculate histograms**

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Color

Grayscale

Feature Extraction

Convert image to HSV and extract value channel → Crop left and right side of image → Calculate histograms

Color

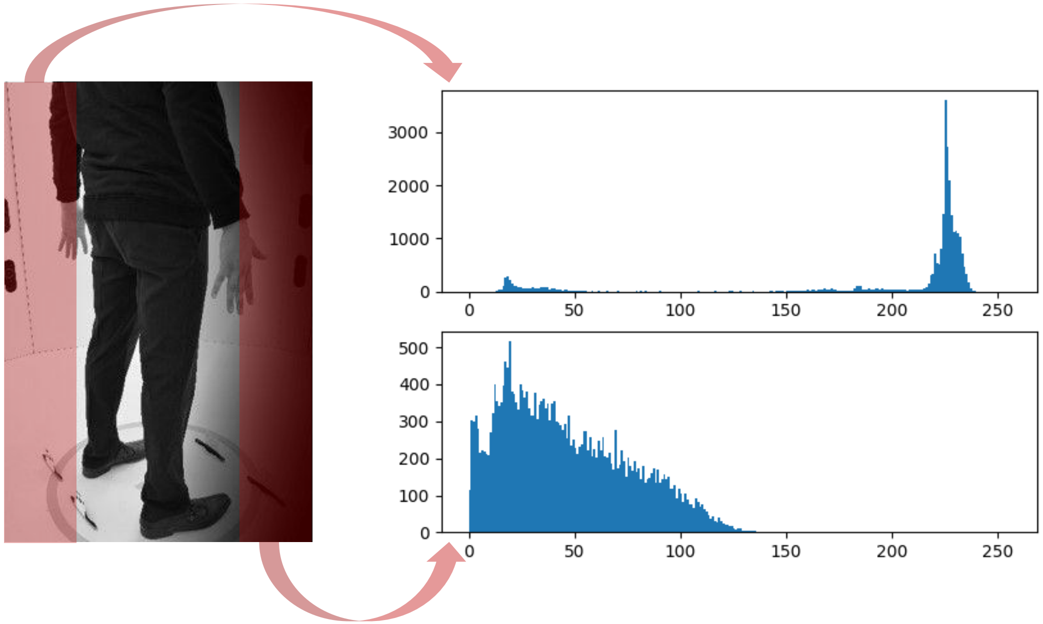
Grayscale

Analysed 4 different crop ratios:

1. 5%
2. 12.5%
3. 25%
4. 40%

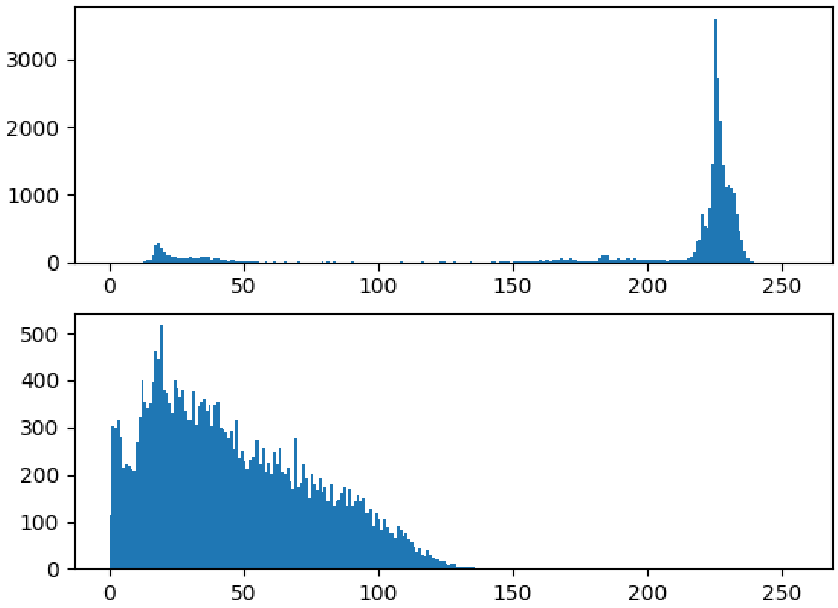
Feature Extraction

Convert image to HSV and extract value channel → Crop left and right side of image → **Calculate histograms**

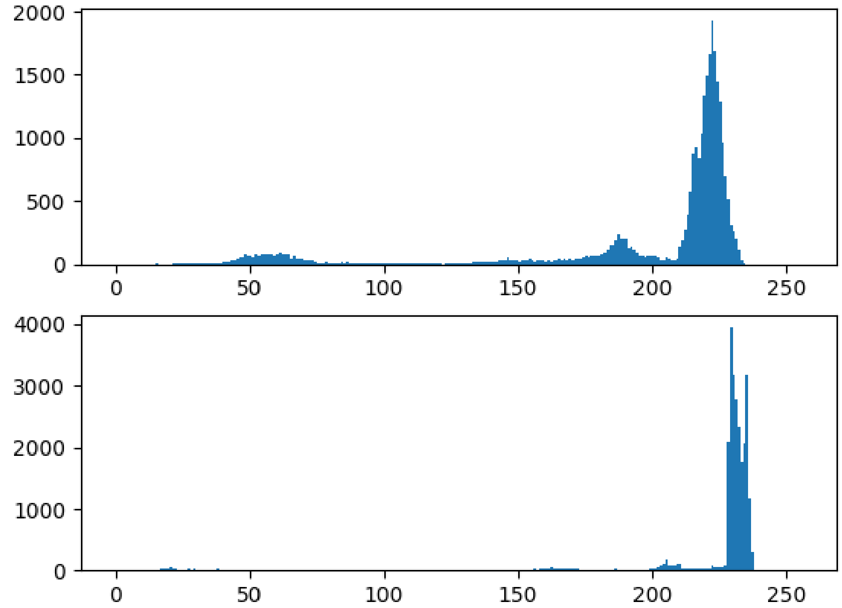


Feature Extraction

MISFIRED IMAGE

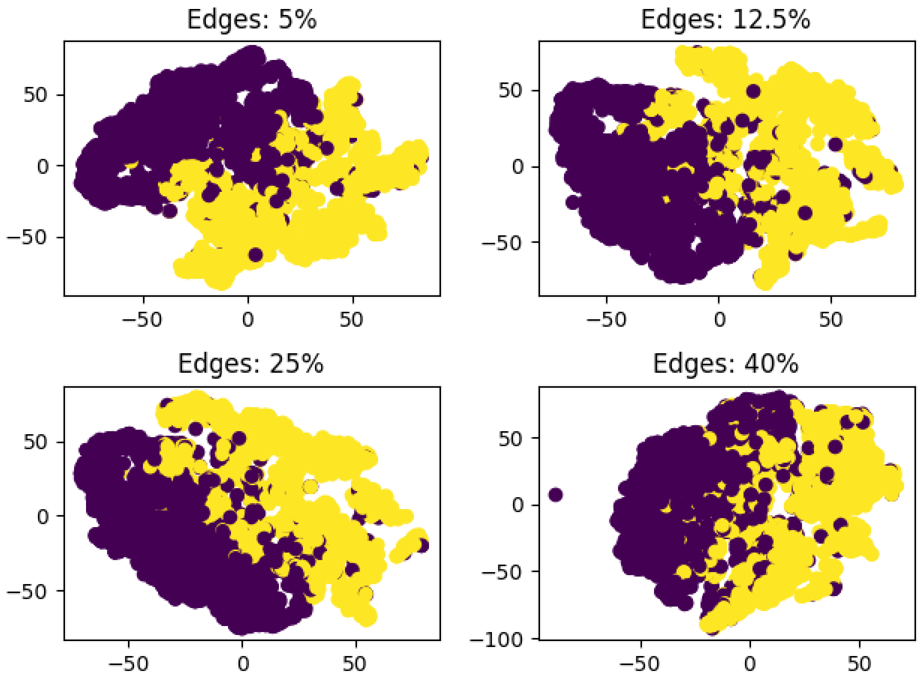


NORMAL IMAGE



t-SNE (t-distributed Stochastic Neighbor Embedding)

- Method for visualizing data set and distribution of classes among different features
- Cropped parts of image at different widths: 5%, 12.5%, 25%, 40%



Model Set-up

- 4 different machine learning methods:
  - k-Nearest Neighbors
  - Support Vector Machines
  - Random Forest
  - Artificial Neural Networks (Multi-layer perceptron)

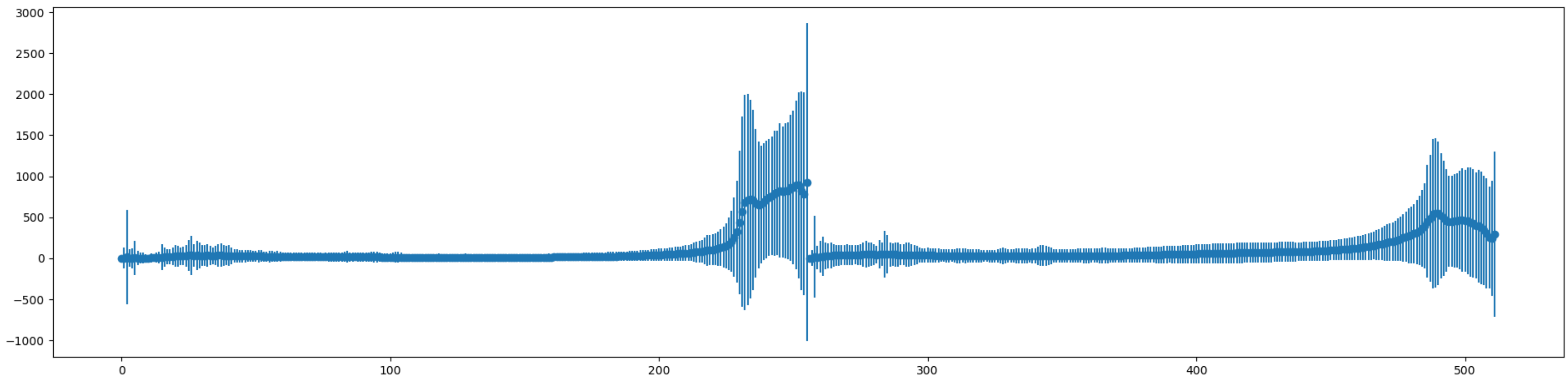
Model Set-up

Standardize data → Set up training and model parameters → Training

Model Set-up

Standardize data → **Set up training and model parameters** → **Training**

- Zero-centered by feature
- Scale by feature variance



Model Set-up

- **k-Nearest Neighbors**
  - Parameters: k-number of neighbors
- **Support Vector Machines**
  - Parameters: kernel, C, gamma
- **Random Forest**
  - Parameters: criteria, number of trees, max depth, minimal samples for split
- **Artificial Neural Network**
  - Parameters: network architecture, optimizer and learning rate, loss function

Model Set-up

Standardize data → Set up training and model parameters → **Training**

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Evaluation

- F1-measure

$$precision = \frac{tp}{tp + fp}$$

$$recall = \frac{tp}{tp + fn}$$

$$F1 = 2 * \frac{precision * recall}{precision + recall}$$

- 11-fold cross validation
- Split on train and test set, 80-20 ratio

Results for k-Nearest Neighbors

- Parameter optimization was done using 11-fold cross validation
- Parameters:
  - k – number of neighbors
  - Euclidean distance

Edge[%]		5	12.5	25	40
k – neighbors	5	**93.69 (+/- 1.41)**	93.65 (+/- 1.29)	92.71 (+/- 2.15)	91.53 (+/- 1.95)
	10	93.17 (+/- 1.96)	93.40 (+/- 2.02)	92.73 (+/- 2.53)	**91.73 (+/- 1.69)**
	15	93.52 (+/- 1.10)	**93.76 (+/- 1.75)**	92.71 (+/- 1.66)	91.68 (+/- 2.20)
	35	92.91 (+/- 2.12)	93.18 (+/- 2.14)	**92.76 (+/- 1.79)**	91.07 (+/- 2.07)

Results for Support Vector Machines

- Parameter optimization was done using 11-fold cross validation
- Best parameters:
  - kernel function: rbf
  - C = 10
  - Gamma = 0.001

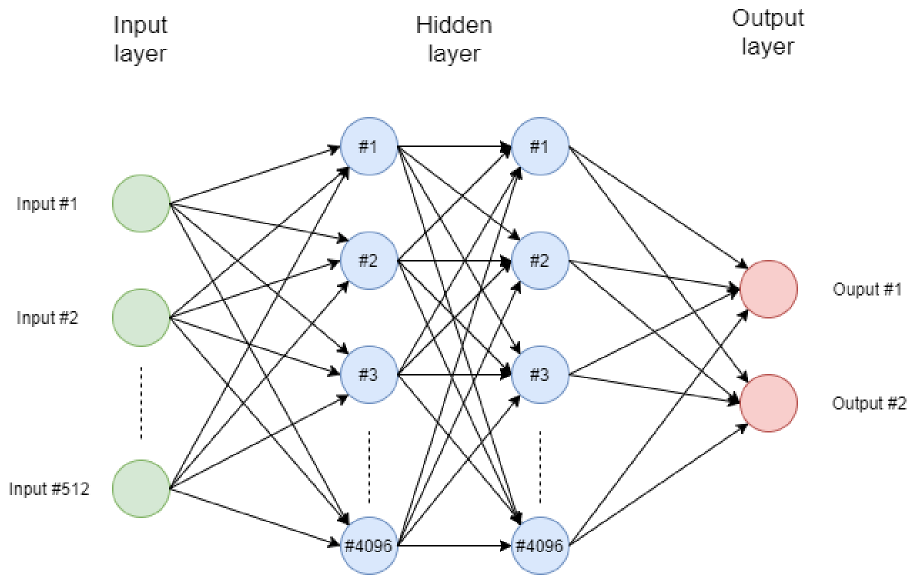
Edge [%]	**5**	**12.5**	**25**	**40**
Accuracy [%]	94.33 (+/- 1.47)	**94.42 (+/- 1.48)**	94.23 (+/- 1.76)	93.53 (+/- 1.61)

Results for Random Forest

- Parameter optimization was done using 11-fold cross validation
- Parameters:
  - criteria, number of trees, max depth, min samples for split

Edge[%]	5	12.5	25	40
Criteria	**gini**	gini	entropy	gini
Number of trees	**64**	512	64	512
Max depth	**512**	512	512	60
Min samples for split	**5**	2	2	2
Accuracy [%]	**94.55 (+/- 1.38)**	94.38 (+/- 1.40)	93.71 (+/- 1.82)	93.51 (+/- 0.95)

Results for ANN (Artificial Neural Network)



Network architecture

- Architecture same as classification block in well-known networks (VGG16, ResNet50, etc.)
- Dropout is increased to 0.75, from regular 0.5
- ReLU activation function in hidden layers
- Softmax function in output layer

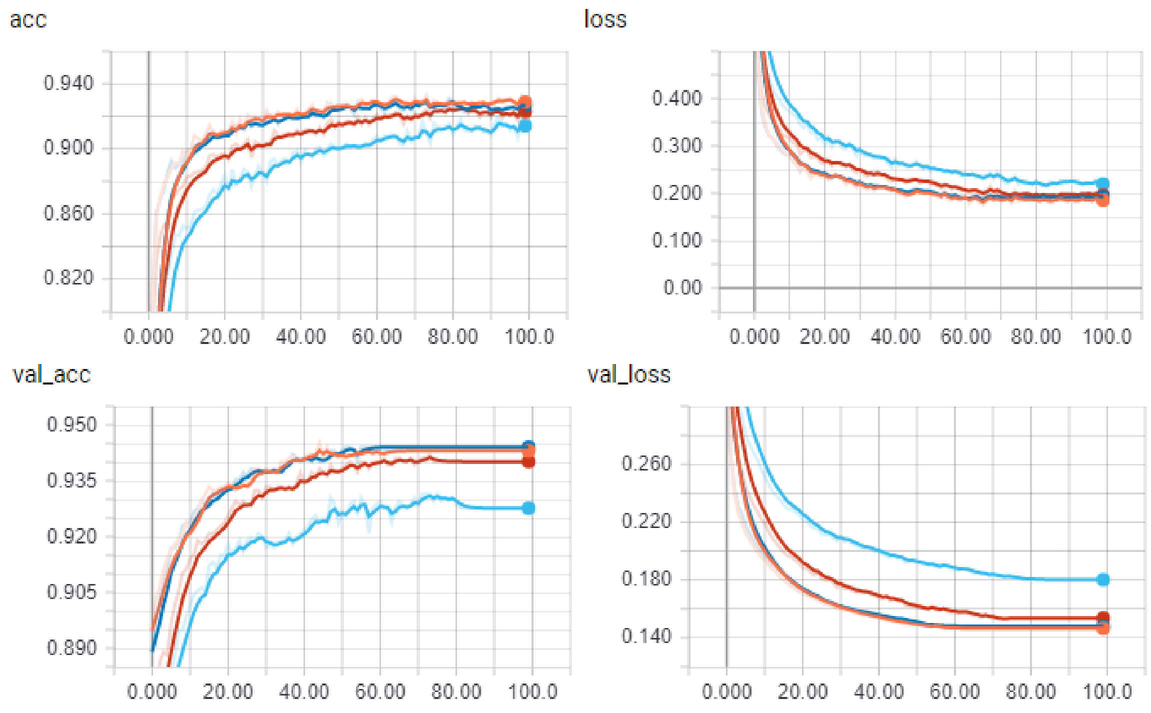
Results for ANN (Artificial Neural Network)

- SGD (Stohastic Gradient Descent)
  - learning rate = 0.0001
  - Momentum = 0.9
  - Nesterov = True
  - Reduce learning rate by factor of 0.1, if value loss haven’t been improved for 2 consecutive epochs
- Training
  - 100 epochs (~1.5h)
- Loss
  - Categorical cross entropy

Edge [%]	5	12.5	25	40
Accuracy [%]	94.47	**94.59**	94.36	93.04

Results for ANN (Artificial Neural Network)

- Training process



Edges: • 5% •12.5% •25% •40%

Final Results

Comparison of proposed methods on test data

Edge [%]	5	12.5	25	40
RF	**95.14**	94.76	94.96	93.60
ANN	94.47 (-0.67)	**94.59 (-0.17)**	94.36 (-0.60)	93.04 (-0.56)
SVM	**94.75 (-0.39)**	94.59 (-0.17)	94.23 (-0.73)	93.40 (-0.20)
k-NN	**94.58 (-0.56)**	94.56 (-0.20)	94.31 (-0.65)	93.40 (-0.20)

Conclusion

- Proposed a method for detecting misfired images
- Based on histograms as global descriptors and machine learning algorithms
- All 4 considered algorithms showed very good and comparable performance
- Random Forest showed best performance with 95.14% accuracy on edge area set to 5%
- **Possible improvements:**
  - Add additional feature descriptors
  - Clear and expand the data set
- **Future work:**
  - Final goal is development of complete quality control system for 3D scanning
  - System is expected to detect: misfiring, empty scene, blur
  - Reconstruction of missing 3D model body parts

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