Akademia Górniczo-Hutnicza
im. Stanisława Staszica w Krakowie
AGH University of Science
and Technology

User-Generated Content (UGC)/In-The-Wild Video Content Recognition[1]

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[1] Supported by Polish National Centre for Research and Development (TANGO-IV-A/0038/2019-00).

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5. For this content, we use the term "in the wild" as a concept closely related to the concept of UGC, which is its special case.
6. In this paper, we show that it is possible to introduce the new concept of an objective "in-the-wild" video content recognition model.

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(a) Professional content with no “in-the-wild” content

(b) Professional content with “in-the-wild” content displayed in small area

(c) Professional content with “in-the-wild” content displayed in large area

(d) “In-the-wild” content with professional content mixed in large area

(e) “In-the-wild” content with professional content mixed in small area

(f) “In-the-wild” content with no professional content

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4. As a result, we get 68 shots with professional content and 2 169 shots with “in the wild” content.

Video Indicators

#	Name
1	Blockiness
2	Spatial Activity (SA)
3	Block Loss
4	Blur
5	Temporal Activity (TA)
6	Exposure
7	Contrast
8	Noise
9	Slicing
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Table: The list of video indicators which are used in the experiment.

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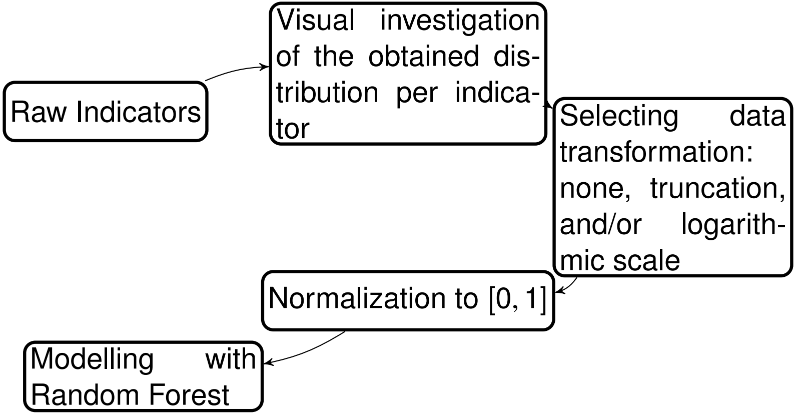

Figure: Data preparation and analysis schema.

Modelling

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#	Name	Truncation	Log	min	max
1	Blockiness	[0.5, 1.25]	no	0.5	1.25
2	Spatial Activity (SA)	[0, 200]	no	0	200
3	Block Loss	none	yes	0	3.33
4	Blur	[0, 22]	yes	0	1.36
5	Temporal Activity (TA)	[0, 75]	no	0	75
6	Exposure	none	no	9	222
7	Contrast	none	no	0	104
8	Noise	none	yes	0	1.79
9	Slicing	none	yes	0.16	4.22
10	Flickering	none	no	0	1

Table: Normalisation procedure for each indicator.

Results

	Accuracy	Precision	Recall	F-measure
Test set	0.956	0.976	0.971	0.973
“In-the-wild” set	0.975	1.000	0.975	0.987

Table: Decision tree results received for “in-the-wild” content recognition.

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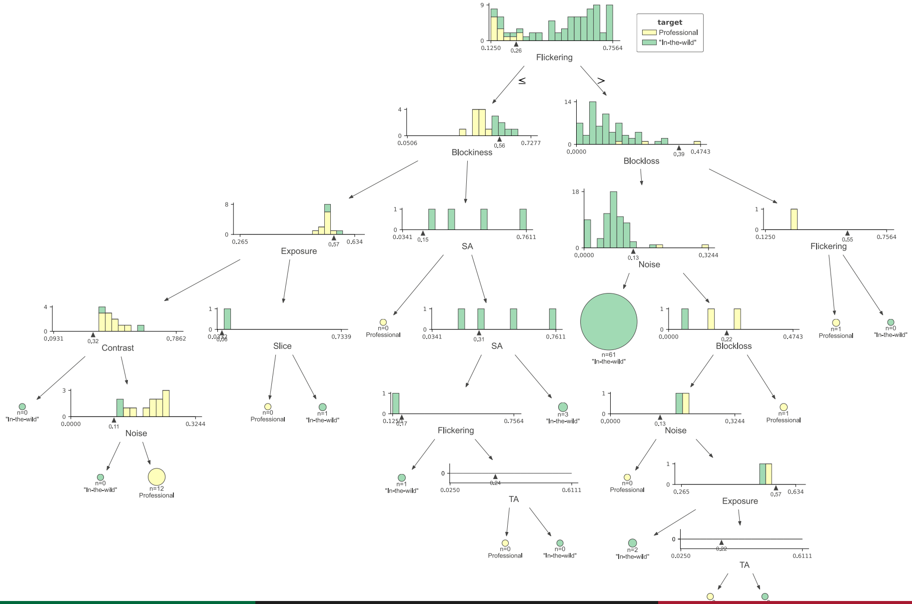
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Professional
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Noise
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Contrast
Slice
n=0
Professional
SA
n=61
"In-the-wild"
Blockloss
n=1
Professional
n=0
"In-the-wild"
Noise
Flickering
n=3
"In-the-wild"
Noise
n=12
Professional
TA
Exposure
n=2
"In-the-wild"
TA

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	Accuracy	Precision	Recall	F-measure
Test set	0.980	0.983	0.994	0.988
“In-the-wild” set	0.994	1.000	0.994	0.997

Table: Random forest results received for “in-the-wild” content recognition.

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6. While the current results are highly promising, they still require additional validation since training and test data sets are relatively limited (especially for professional content).
7. Therefore, additional selected video sequences from the collected database of 6000+ professional YouTube news clips should be used.

Publication

Mikołaj Leszczuk, Lucjan Janowski, Jakub Nawała, and Michał Grega, "User-Generated Content (UGC)/In-The-Wild Video Content Recognition", 14th Asian Conference on Intelligent Information and Database Systems, November 28-30, 2022, Ho Chi Minh City, Vietnam