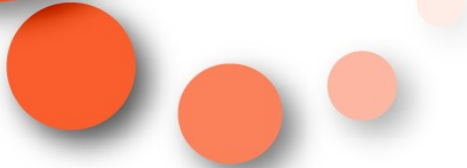
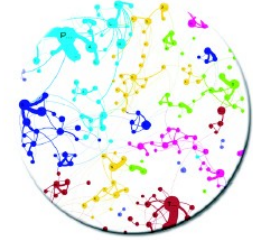




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Mining tortured acronyms from the scientific literature

Alexandre Clause, Guillaume Cabanac, Pascal Cuxac, Cyril Labbé

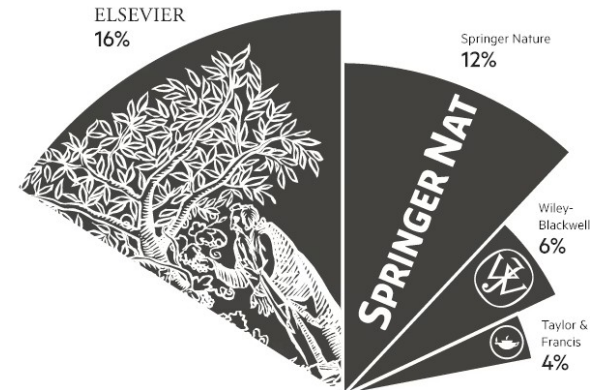


Publish or perish



Elsevier top of the league

Global market share of journal articles by leading publishers, 2013 (%)



Source: company

<https://www.ft.com/content/93138f3e-87d6-11e5-90de-f44762bf9896>

voice recognition

deep neural network



Convolutional Neural Network. Artificial Neural Networks with numerous layers are termed as Deep Neural Networks or Deep Learning. It has been explored as one another key resource in recent years and has become quite well recognized in the literary community because of its efficiency to manage with huge amounts of data [17]. The most well-known **profound neural network** is the Convolutional Neural Networks (CNNs), which takes its name from operation of mathematical dimension from the matrixes termed convolution. Convolutional Neural Network (CNN) has various types of layers; it includes pooling, nonlinearity, and convolutional and fully connected layers. Convolutional Neural Network has pivotal outcomes over previous decades in an assortment of fields identified with **design acknowledgment** from picture handling to **voice acknowledgment** [8]. The significant part of CNN is to get theoretical highlights when information proliferates towards the more **profound layers**. For instance, in picture characterization, the edge may be distinguished in the principal layers, and afterward the less difficult shapes in the subsequent layers, and afterward the **more elevated level highlights**.

pattern recognition

deep layers

high-level features

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Tortured phrases

spectral local linearization method



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The spectral local linearization method. The unearthy neighborhood linearization technique (SLLM) can be used to unravel an arrangement of the non-comparable conditions. Within this method the criteria for logarithmic criteria are linearized using thoughts similar to the Gauss–Seidel approach.



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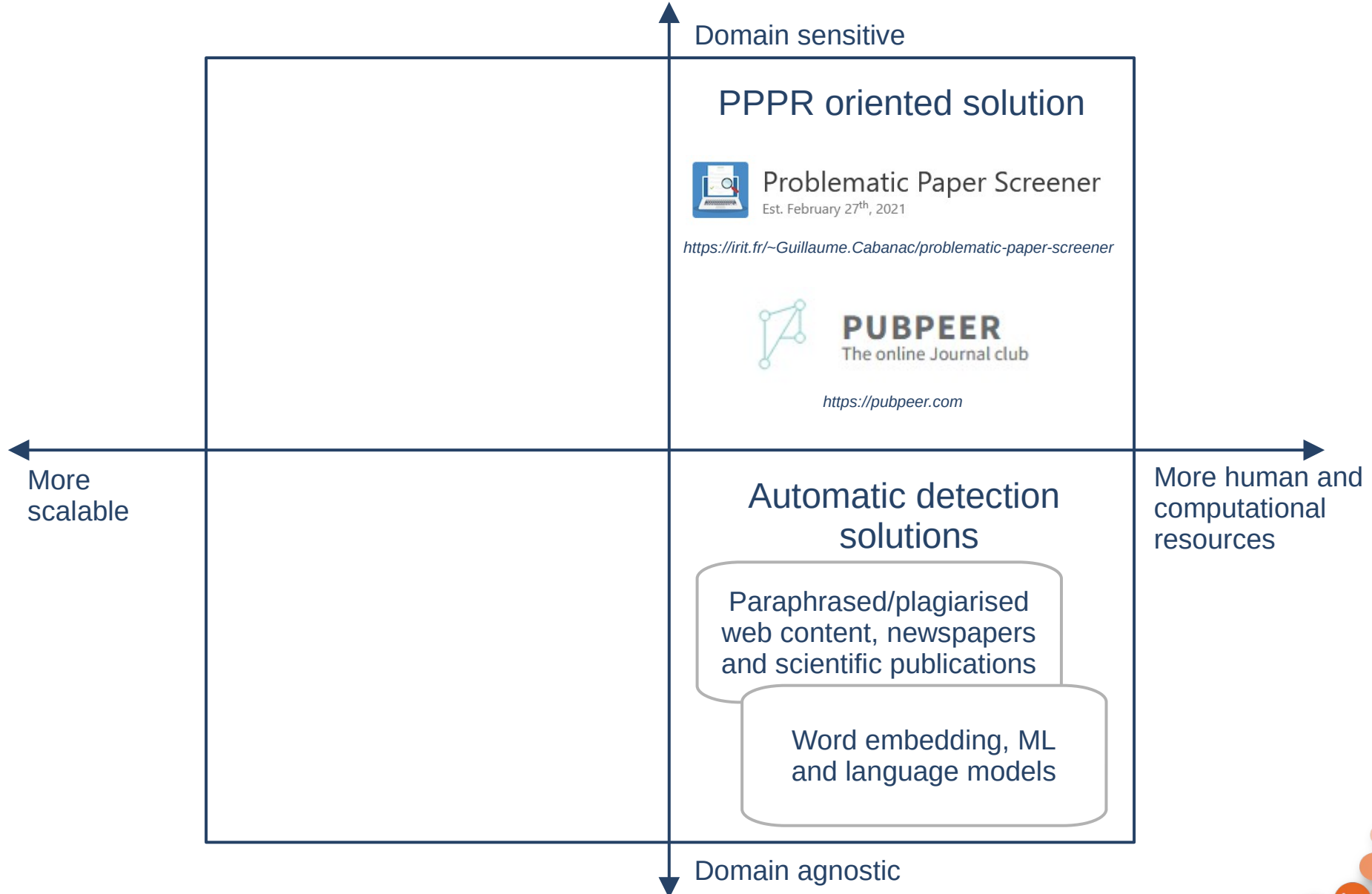
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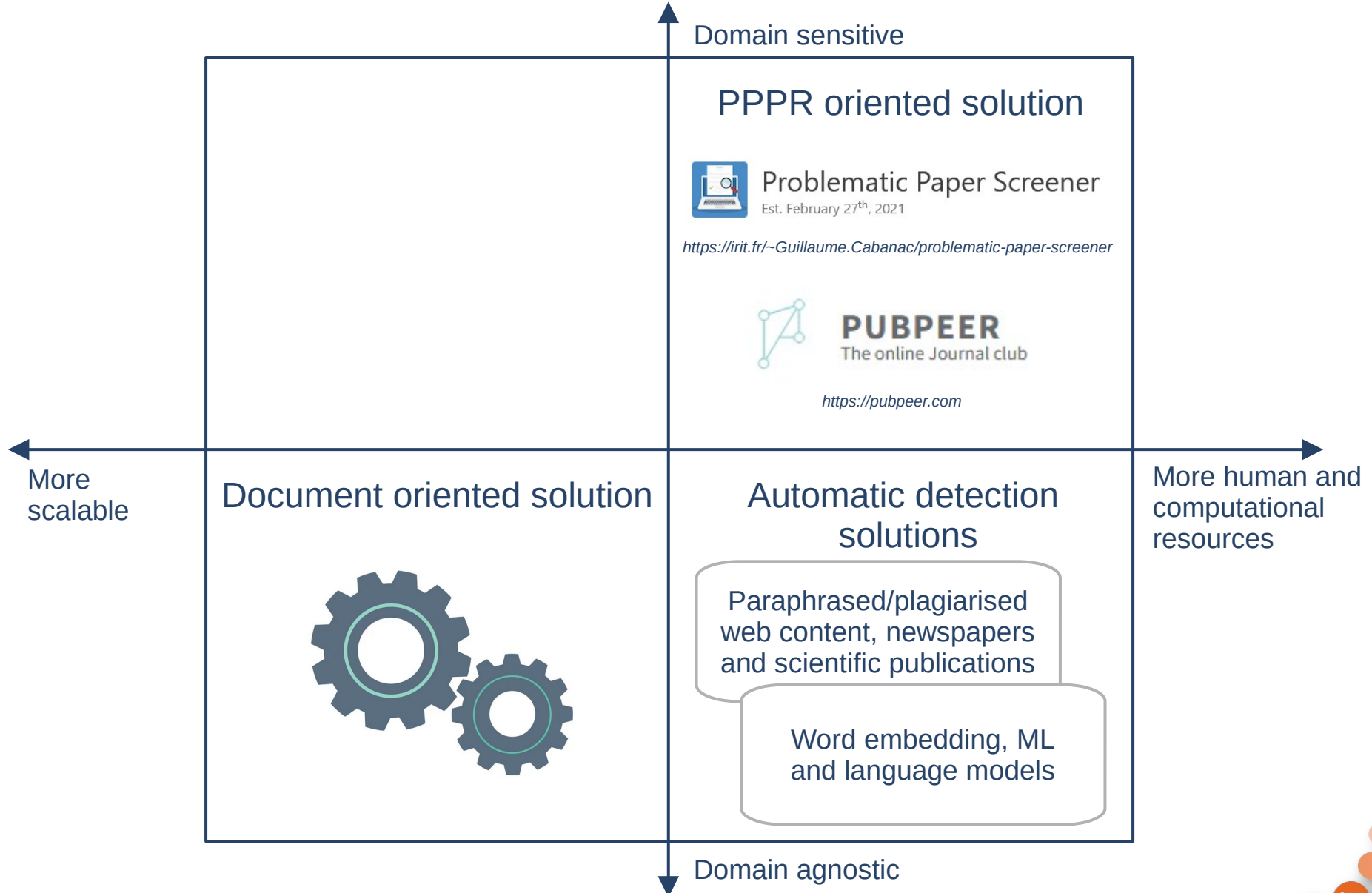
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(snapshot taken on May 21, 2024)

Existing solutions

Existing solutions

Proposed solution



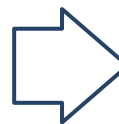
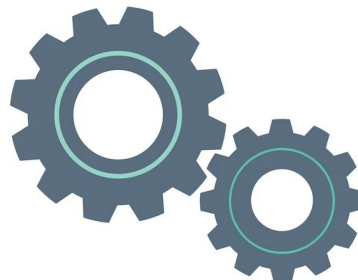
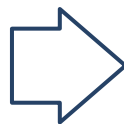
Draft



Preprint



Article



Submission (authors)

Editorial workflow (publishers)

Decision making (editors)

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A half breed framework is introduced in which a convolutional neural organization and a logistic Relapse Classifier are consolidated. Discriminant investigation is more effective when the ordinariness suspicious are fulfilled. The thoughts are finished on Yale face information base shows improved arrangement rates in more modest measure of time [10]. Class Activated Mapping Great-CAM is utilized to show the areas that our organization uses to segregate between [11].

Dense SIFT and customary SIFT are considered in [12] and contrasted when combined and CNN highlights. Besides, an aggregator of the models is created. Results show the prevalence of CNN with Dense SIFT over ordinary CNN and CNN with SIFT. The exactness even expanded when all the models are collected which produces condition of confidence results on 73.4% and 99.1% on FER-2013 and CK- respectively.

We propose a grouping technique, called the **closest component line (NFL)** for face acknowledgment. Any two component purposes of individual face membership by the element line (FL) going through the two focuses. The infers FL can catch big number of faces of office pictures than the first focuses and in this manner extends the limit of the accessible information base. The characterization depends on the closest separation from the question include highlight every FL. With a consolidated face information base, the NFL mistake rate is about 43.7-63.4% of that of the standard eigenface technique. Besides, the NFL accomplishes the most reduced mistake rate and answered to date for the ORL face information base [13].

The current works fail to announce the CNN designs that function admirably for face acknowledgment instead of examine the explanation. In this network, we address this issue: present CNN-based face acknowledgment frameworks (CNN-FRS) on a shared belief to make our work effectively reproducible. The three principal structures of CNN designs were utilizing LFW information. This paper quantitatively thinks about the designs of CNNs and assesses the impact of various usage decisions. We recognize a few helpful hypotheses of CNN-FRS. For example, the dimensionality of the **scholarly highlights** can be altogether decreased without unfriendly impact on face acknowledgment exactness. Likewise, a conventional measurement learning technique showing CNN-learned highlights is assessed. Analyses show two critical components to great CNN-FRS execution are the combination of numerous CNNs and metric learning [14].

A convolution neural organization (CNN) with **consideration instrument** that can see the impediment districts of the face and spotlight on the most discriminative unblocked locales. Thinking about various ReLU, we present two realizations of ACNN: aACNN just focuses on neighborhood facial patches, aACNN incorporates nearby portrayals at fix level with worldwide portrayal aspect level. Trial results show that ACNNs improve the acknowledgment precision on both the non-impediment and blocked countenance. Perception results show that, contrasted and the CNN without Gate Unit, ACNNs are fit for moving the consideration from the blocked patches to other related yet unimpeded ones. ACNNs additionally outperform other best-in-class techniques on face recognition in the labourer appearance datasets under the cross-dataset assessment convention [15].

With the quickly advancement of the face acknowledgment (FR), warm face acknowledgment has gotten expanding consideration in any case, the conventional techniques for warm face acknowledgment for the most part focus on the hand-made component plan, which requires more endeavour. For example, face-based systems are proposed to recognize faces with moderately lower acknowledgment rate. A convolutional neural organization (CNN) design for warm face acknowledgment is presented. CNN is another kind of neural organization strategy which can consequently take in viable highlights from the study information. Investigation results on FER-2013 face information base show that our proposed CNN engineering accomplishes higher acknowledgment rate contrasted and the customary acknowledgment, for example, LBP, HOG and minutiae invariant [16].

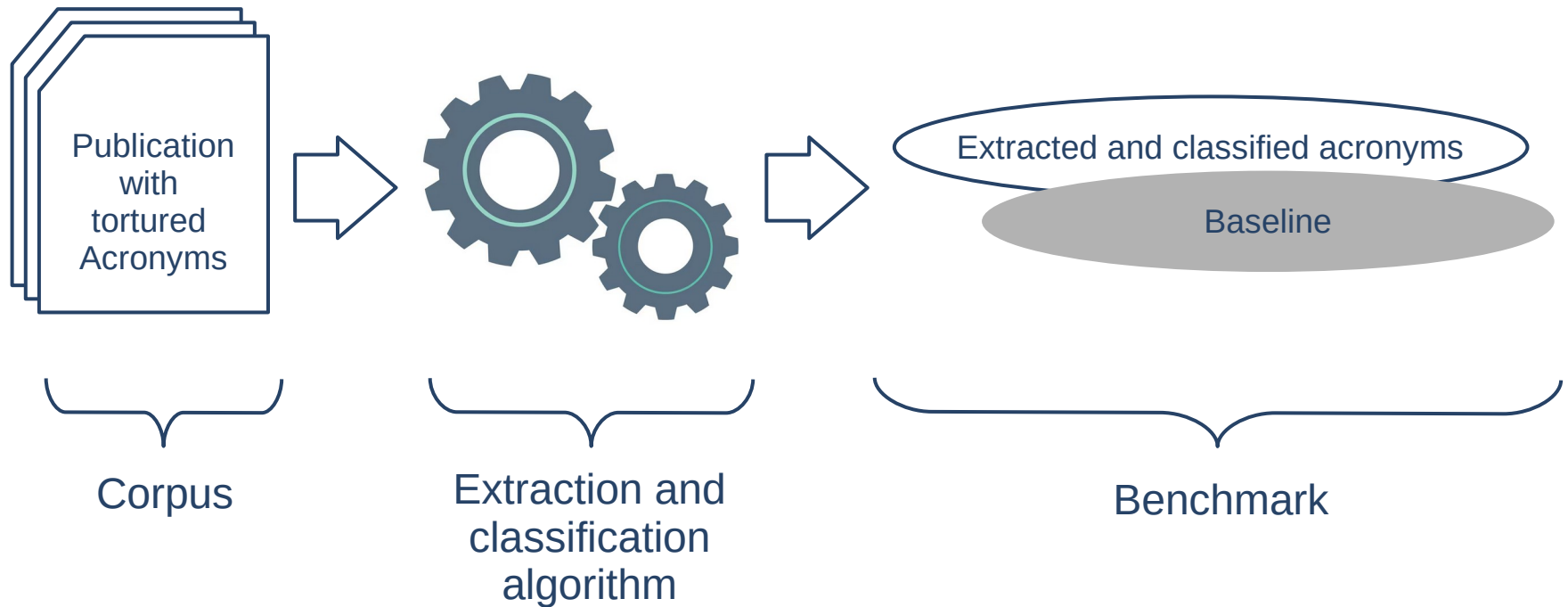
Video-based feeling acknowledgment framework joins imperative neural organization (RNN) and 3D convolutional networks (3D) in a late-combination style. RNN and 3D encode appearance and movement data in an unexpected way. In particular, RNN takes appearance highlights removed by convolutional neural organization (CNN) over individual video outlines as info and encodes movement later, while 3D models appearance and movement of video at the same time. Joined with a sound module, our framework accomplished an acknowledgment exactness of 59.02% without utilizing any extra feeling marked video cuts preparing set, contrasted with 53.8% of the state-of-the-art in 2015. Broad examinations show that consolidating RNN and 3D together can improve video-based feeling acknowledgment perceptibility [17].

Perceiving human appearances is quite possibly the most well-known issues in the field of computer acknowledgment. Numerous methodologies and strategies have been tried and applied on the theme, particularly neural organizations. This paper proposed another method that can be supplemented at the lower part of a neural organization engineering as far as face acknowledgment, called **obedient multi-scale layer (MSL)**. To make more sure forecasts and arrangements, this **invariant layer** helps the **profound learning** model to indicate further discernible groups between various individuals (classes) by setting additional requirements on pictures of $k \times k$ similar individual (multi-individual) while putting edges on pictures of $n \times n$ between individual (between individual). This proposed obedient **multi-scale layer** improved the acknowledgment exactness on countenances by 2% [19].

Face acknowledgment is critical to certifiable applications, for example, video observation, human machine connection and security frameworks. When contrasted with conventional AI (draw, net), **profound learning** based techniques have indicated better exhibitions regarding precision and speed of preparing in picture acknowledgment. This paper proposes an altered Convolutional Neural Network (CNN) design by adding two standardization activities to two of the layers. The standardization activity which is bunch standardization gave increasing speed of the organization. CNN design was utilized to extract particular face highlights and Softmax classifier was utilized to characters faces in the **completely associated layer** of CNN. In the trial part, Georgia Tech Database indicated that the proposed approach has improved the **face acknowledgment exactness** with better acknowledgment results [21].

Face pictures showing up in sight and sound applications such as secure payment systems through cloud [21] [22], informal organizations and computerized management ordinarily display emotional posture, brightening, and appearance varieties, bringing about significant execution debasement for conventional face acknowledgment calculations. This paper proposes a complete **profound learning** structure to get the deep face portrayals from the data. The proposed **profound learning** structure is made out of a bunch of extravagantly planned convolutional neural organizations (CNNs) and a three-layer stacked auto-encoder (SAE). The arrangement of CNNs separate consecutive **facial highlights** from multi-dimensional information. At that point, these extracted highlights are connected to frame a high-dimensional component vector, whose measurements compacted by SAE. The entries of the CNN are prepared utilizing a subset of 2000 subject from the face image database CASIA-Web Face Information Base which comprises of 100000 face images.

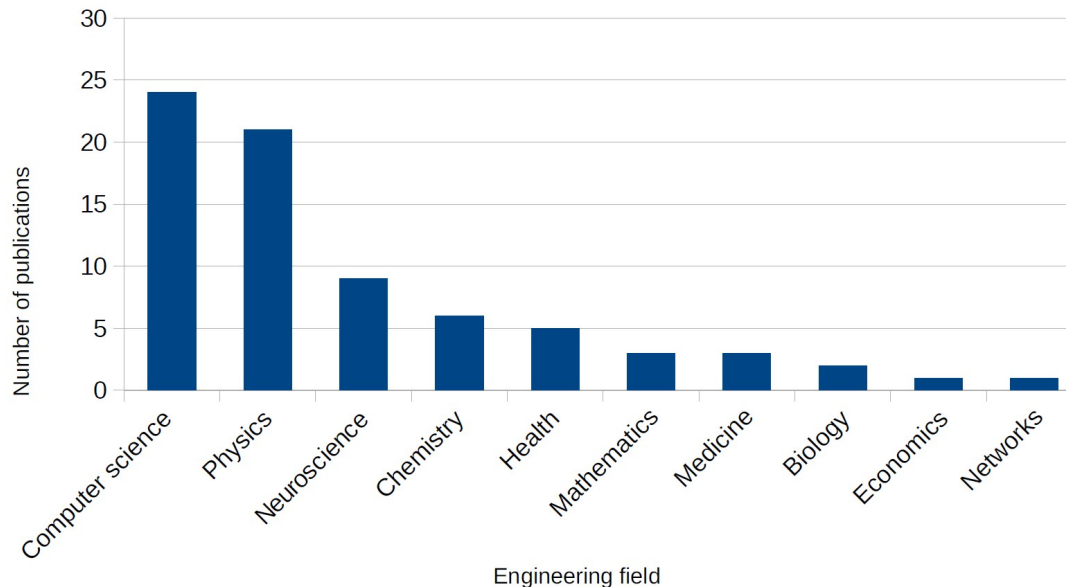
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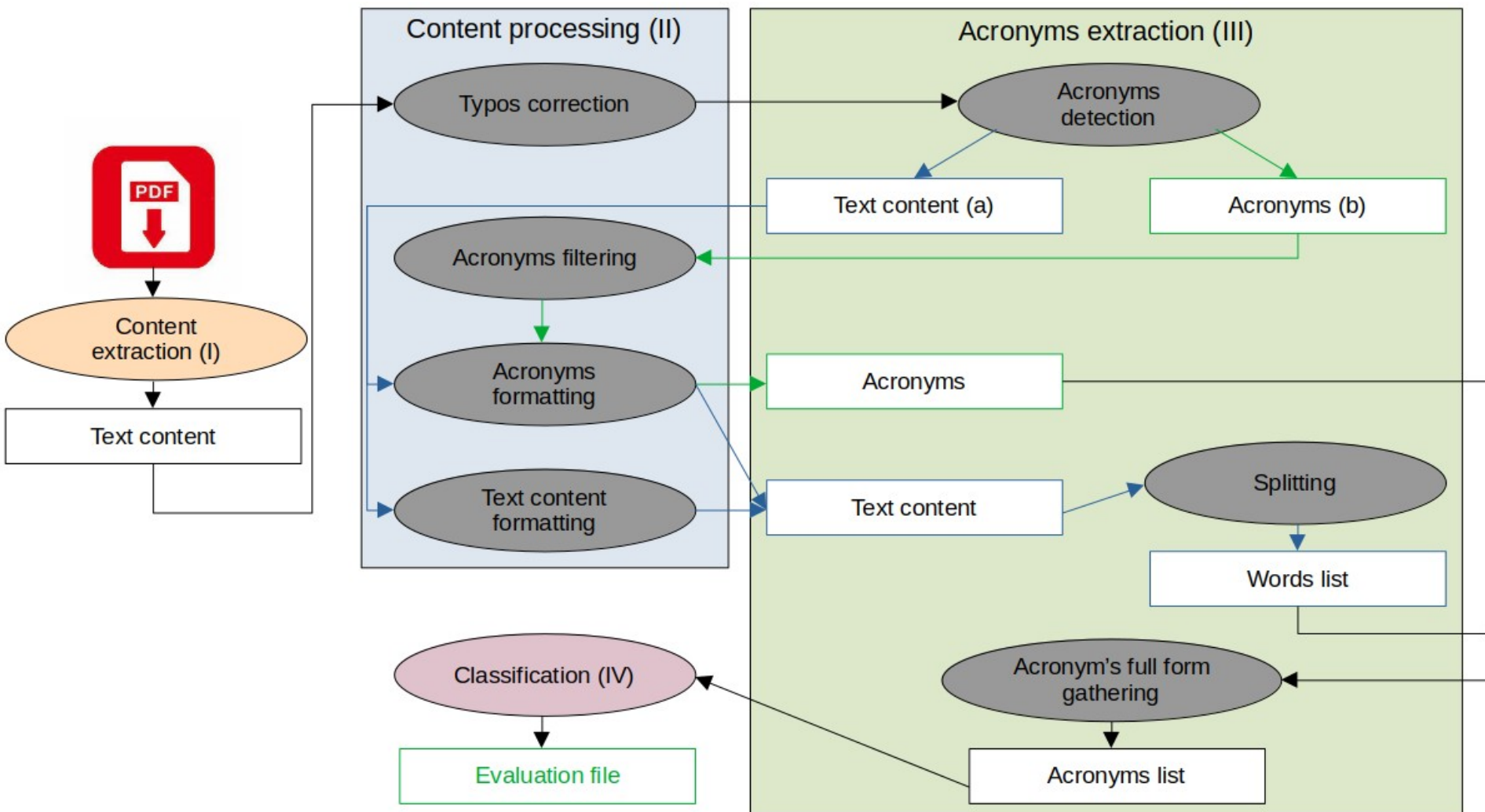


Bolster Vector Machine (SVM) → *Support* Vector Machine (SVM)

- 75 open access publications
- Published between 2015 and 2023
- 37 multidisciplinary publications
- 995 acronyms
- 366 tortured acronyms (36.8%)
- 46 invalid acronyms (4.6%)

<http://doi.org/10.5281/zenodo.10492230>





Characteristic	Class	
	Genuine	Tortured
(1) Same amount of initials	<i>Hidden Markov Model (HMM)</i>	<i>Concealed Markov Display (HMM)</i>
(2) Different amount of initials	<i>Generalised Linear Model (GLM)</i>	<i>Summed Up Direct Models (GLM)</i>
(3) Compounds	<i>Multidrug Resistance (MDR)</i>	<i>Multidrug Safe (MDR)</i>
(3) Chemicals	<i>Diethylenetriamine Pentaacetic acid (DTPA)</i>	<i>Diethylenetriamine Pentaacetic ruinous (DTPA)</i>
(4) Reduced forms	<i>Residual neural Network (ResNet)</i>	<i>Lingering brain Organization (ResNet)</i>

Characteristic	Class
(1) Same amount of initials	// (1) no offset using <u>Hidden Markov Model</u> (HMM) using <u>Concealed Markov Display</u> (HMM) → Genuine → Next step
(2) Different amount of initials	
(3) Compounds	// (2) no offset <u>the Moroccan Agency of Press</u> (MAP) → Genuine <u>the Moroccan Organization of Press</u> (MAP) → Next step
(3) Chemicals	
(4) Reduced forms	// (1) 1 token offset <u>Hidden Markov Model</u> architecture (HMM) → Genuine <u>Concealed Markov Display</u> architecture (HMM) → Next step
	// (2) 1 token offset <u>Center for Disease Control and Prevention</u> (CDC) → Genuine <u>Center for Illness Control and Prevention</u> (CDC) → Next step
	// (3) <u>[...] Multidrug Resistance [...]</u> (MDR) → Genuine <u>[...] Multidrug Safe [...]</u> (MDR) → Next step
	// (4) <u>[...] Residual Network [...]</u> (ResNet) → Genuine <u>[...] Lingering Organization [...]</u> (ResNet) → Tortured

- **Recall (R)** : $TP / (TP + FN)$
- **Precision (P)** : $TP / (TP + FP)$
- **F-score (F1)** : $2 * (P * R) / (P + R)$
- Invalid acronyms are considered as genuine

Acronyms extraction		
	Annotation	Prediction
TP	Acronym	Acronym
FP	-	Acronym
TN	Acronym	-
FN	-	-

Acronyms classification		
	Annotation	Prediction
TP	Tortured	Tortured
FP	Genuine	Tortured
TN	Genuine	Genuine
FN	Tortured	Genuine

Tortured acronyms extraction		
	Annotation	Prediction
TP	Tortured	Tortured
FP	Genuine	Tortured
	Genuine	-
TN	-	Tortured
	Tortured	Genuine
FN	Tortured	-
	-	Genuine
FN	-	-

Task	Recall	Precision	F1
Extraction	0.99	0.89	0.94
Classification	0.95	0.79	0.86
Tortured acronyms extraction	0.93	0.62	0.74

- Domain agnostic
- Scalable
- PDF-oriented
- No need for fingerprints
- Found 185 new fingerprints for the PPS

- Rework the filtering rules (hallucinated and polysemic expressions)
- From silver to gold standard
- Compute weighted evaluation metrics
- Evaluate the pipeline on a new dataset

The case of IOP Publishing:

- Publications between 2017 and 2023
- 3848 problematic publications
- 10% of problematic publications are tortured
- At least 7% contain tortured acronyms

Source: the PPS (consulted on May 21, 2024)

Hallucinated acronym: *Bolster* Vector Machine (BVM) → *Support* Vector Machine (SVM)

Polysemic expression: *Profound Learning*

Perspectives



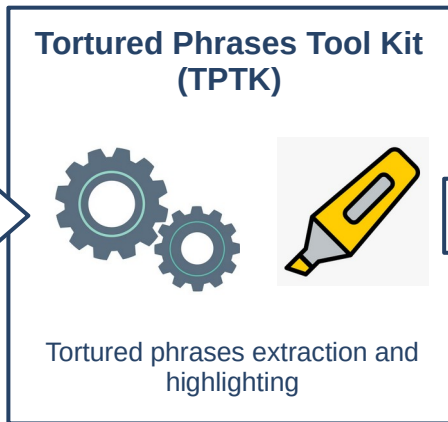
Draft



Preprint



Article



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Brood examinations show that consolidating RNN and 3D together can improve video-based feeling acknowledgment perceptibility [17].

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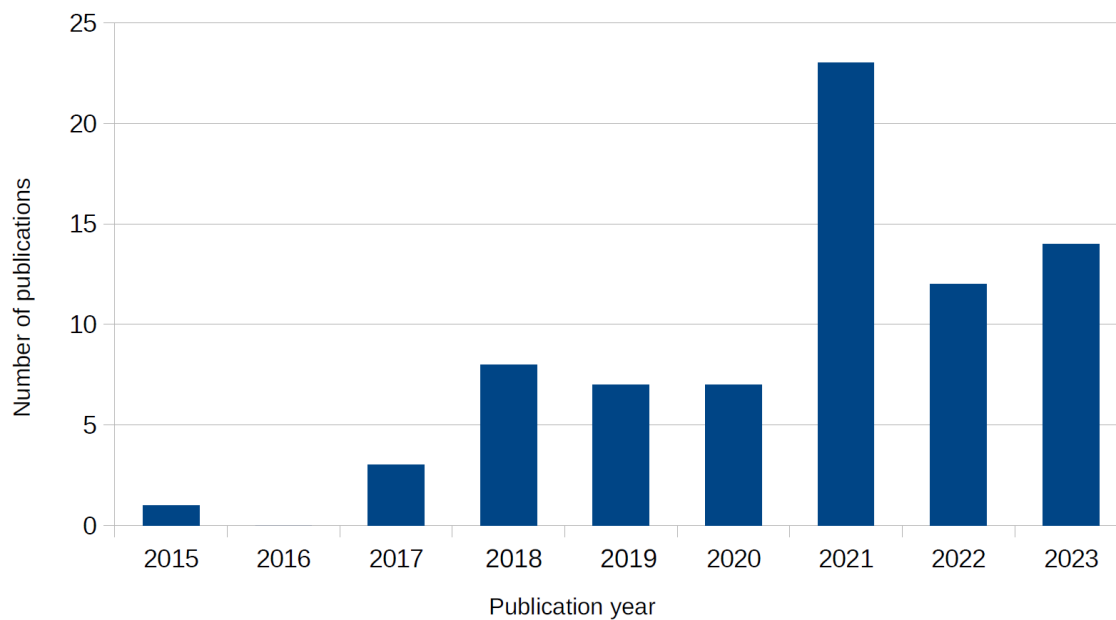
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Submission (authors)

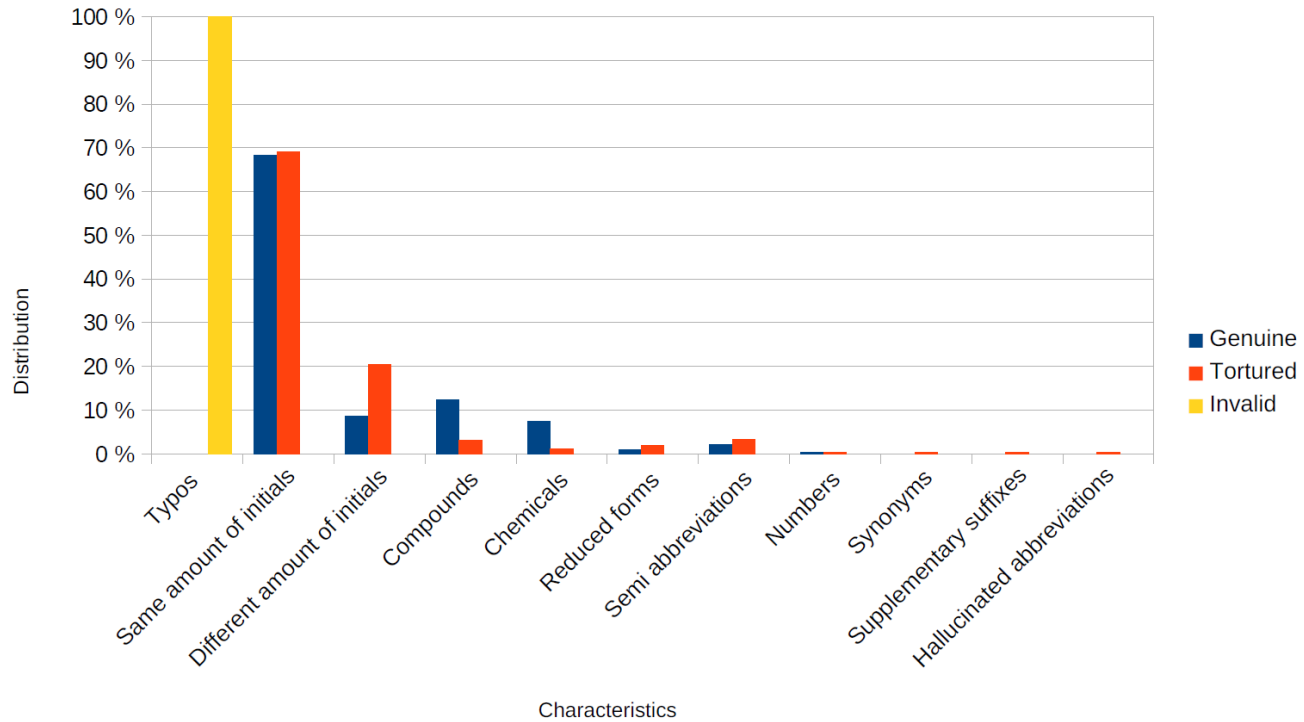
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Decision making (editors)

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Characteristics	Class		
	Genuine	Tortured	Invalid
Typos	-	-	Tru_-Positive (TP)
Same amount of initials	<i>Pain Dysfunction Syndrome (PDS)</i>	<i>Concealed Markov Display (HMM)</i>	-
Different amount of initials	<i>Centers for Diseases Control and Prevention (CDC)</i>	<i>Summed Up Direct Models (GLM)</i>	-
Compounds	<i>Intraocular Pressure (IOP)</i>	<i>Multidrug Safe (MDR)</i>	-
Chemicals	<i>3-Aminopropyltriethoxysilane (3-APTES)</i>	<i>Diethylenetriamine Pentaacetic ruinous (DTPA)</i>	-
Reduced forms	<i>Residual neural Networks (ResNets)</i>	<i>Lingering brain Organization (ResNet)</i>	-
Semi-abbreviations	<i>Gabor-HOG (GHOG)</i>	<i>Non-straight ARMA models (NARMA)</i>	-
Numbers	<i>Three-Dimensional (3D)</i>	<i>Fifth-Age (5G)</i>	-
Synonyms	-	<i>Human PC Interface/Cooperation</i>	-
Supplementary suffixes	-	<i>PC Assisted Determination (CADx)</i>	-
Hallucinated abbreviations	-	<i>Bolster Vector Machine (BVM)</i>	-



Task	Recall	Precision	F1	MCC
Extraction	0.99	0.89	0.94	-
Classification	0.95	0.79	0.86	0.78
Tortured acronyms extraction	0.93	0.62	0.74	-

