CONSTRUCTION ACCIDENT REPORT CLASSIFICATION

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INTRODUCTION

According to the ILO, about 2.78 million workers die annually from occupational accidents, with one in six occurring in the construction industry.

Following an accident, detailed **reports** are usually compiled, which include also unstructured narrative data. Their unstructured nature poses considerable challenges for analysis and knowledge extraction.

The objective of this project is to develop a **classification model** capable of assigning **construction accident reports** to their **correct category**.

<table>
<tr><td colspan="6">Accident: 114404.015 - Employee Falls From Roof And Dies From Multiple Injuries</td></tr>
<tr><td>Open Date</td><td colspan="2">Establishment Name</td><td>End-Use</td><td>Project Type</td><td>…</td></tr>
<tr><td>03/13/2019</td><td colspan="2">Hough Roofing, Inc.</td><td>Commercial building</td><td>Maintenance or repair</td><td>…</td></tr>
<tr><td colspan="6">At 4:00 p.m. on March 12, 2019, Employee #1, employed by a roofing company, was engaged in roofing work at a two-story commercial building... It began to rain slightly. Employee #1 fell, a fall height of 23.5 feet… Employee #1 died later that night from his injuries.</td></tr>
<tr><td colspan="6">Keywords: roofer, fall, fall protection, construction, …</td></tr>
<tr><td>Employee #</td><td>Age</td><td>Sex</td><td>…</td><td colspan="2">Construction</td><td>Inspection</td></tr>
<tr><td>1</td><td>52</td><td>M</td><td>…</td><td colspan="2">FatCause: Fall from roof</td><td>1384743.015</td></tr>
<tr><td colspan="7">Inspection: 1384743.015 - Hough Roofing, Inc.</td></tr>
<tr><td colspan="7">Violation Items</td></tr>
<tr><td>ID</td><td>Type</td><td colspan="2">Standard</td><td>Curr$</td><td>Init$</td></tr>
<tr><td>01001</td><td>Serious</td><td colspan="2">19260501 B11</td><td>$11,934</td><td>$13,260</td></tr>
<tr><td>01002</td><td>Serious</td><td colspan="2">19260503 A01</td><td>$2,652</td><td>$5,304</td></tr>
<tr><td colspan="6">…</td></tr>
</table>

DATASET

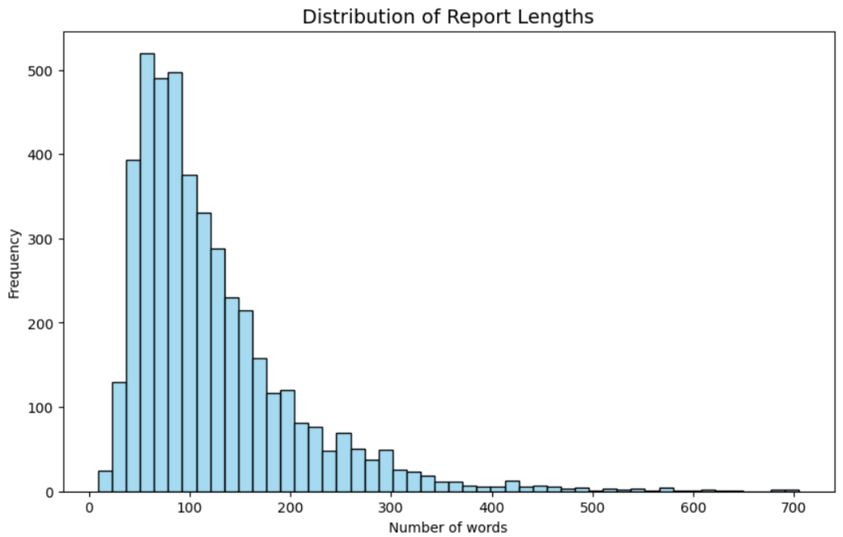
4,770 construction accident reports from the Occupational Safety and Health Administration (OSHA).

There are several fields, but we are interested in the following:

• **title and SUMMARY**: The title and the narrative text describing the details of the accident;

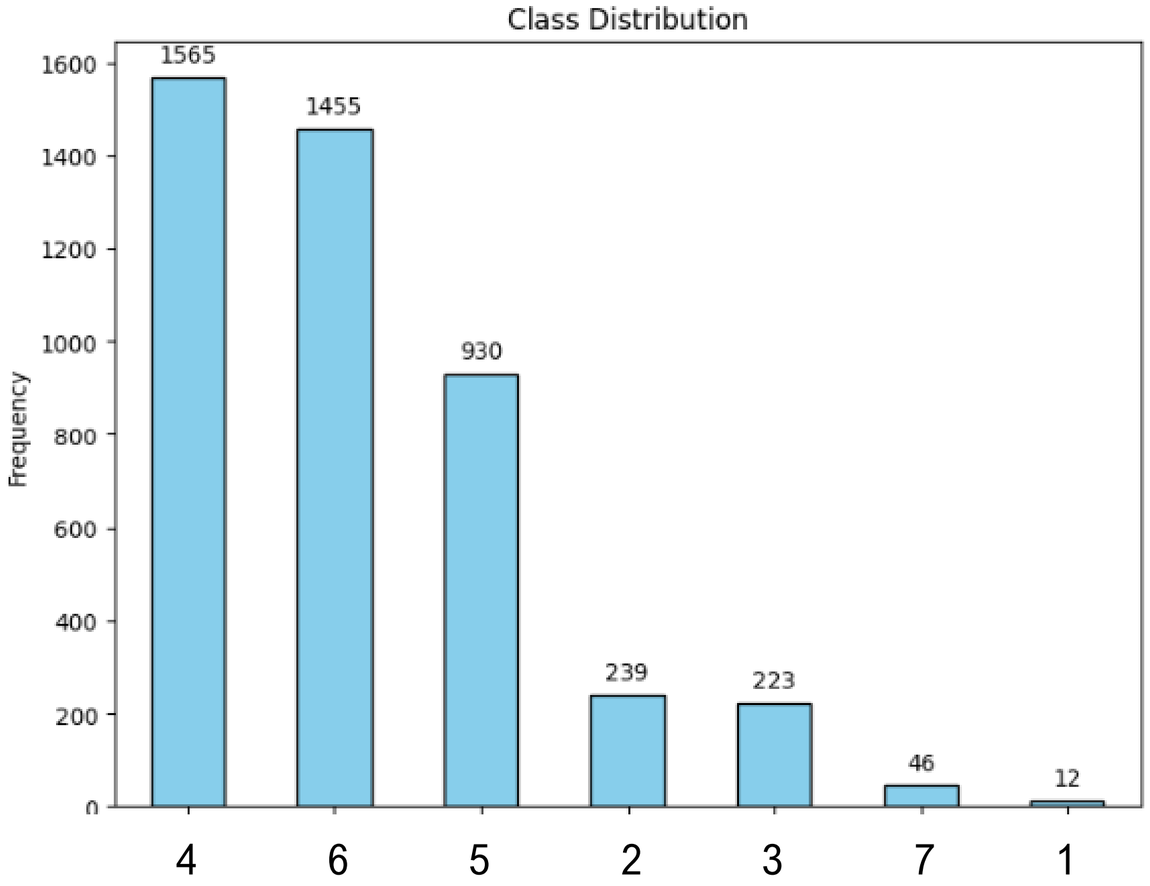
• **TaggedL1**: This is the primary label of the accident. There are seven distinct categories:

– 1 VIOLENCE AND OTHER INJURIES BY PERSONS OR ANIMALS
– 2 TRANSPORTATION INCIDENTS
– 3 FIRES AND EXPLOSIONS
– 4 FALLS, SLIPS, TRIPS
– 5 EXPOSURE TO HARMFUL SUBSTANCES OR ENVIRONMENTS
– 6 CONTACT WITH OBJECTS AND EQUIPMENT
– 7 OVEREXERTION AND BODILY REACTION



CLASS DISTRIBUTION

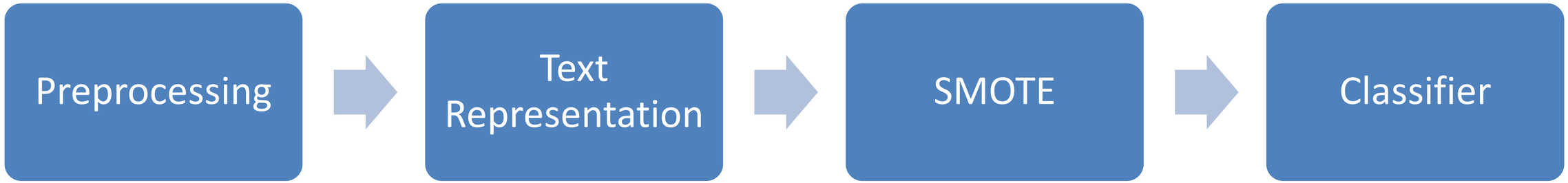
- Highly **imbalanced problem;**
- Class overlap, especially for minority classes (harder to recognize them) [1][2].



DATA PREPARATION

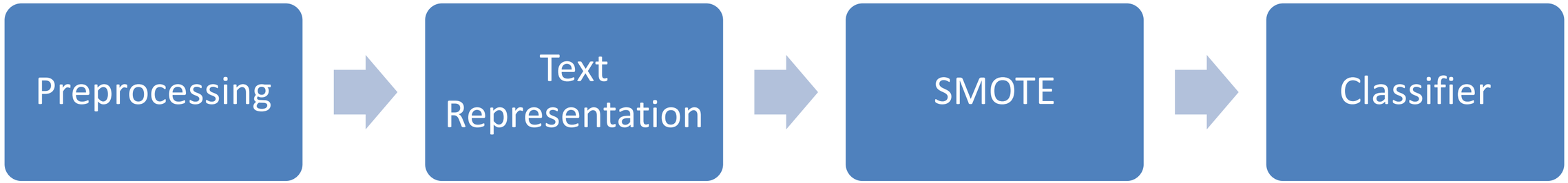
- Combined the **title** and **SUMMARY** fields to create the input texts (**X**);
- Used **TaggedL1** as the target labels (**y**);
- Performed a 70/30 train – test split.

PIPELINE BUILD



- Tokenization;
- Convert to lowercase;
- Removal of punctuation and stopwords;
- Stemming.

PIPELINE BUILD



- Word Embedding: Word2Vec
- Text Vectorizer: Weighted Class TF-IDF[3]

TEXT REPRESENTATION

WCTF-IDF Algorithm (Weighted-Class TF-IDF)

1. Set `f` as the maximum total number of features.

2. Sort classes in descending order by document frequency.

3. For each class `i`:
   - Compute number of features to assign:
     $f_i = f \times (n_i / n)$
     where:
       n_i = number of documents in class i,
       n = total number of documents.
   - Fit a TF-IDF vectorizer on class i documents using f_i as max_features.
   - Save the vocabulary extracted for class i.
   - Pass selected terms as stopwords to the next class to reduce overlap.

4. Merge all class-specific vocabularies into a unified set.

5. Fit a final TF-IDF vectorizer on the entire dataset using the merged vocabulary.

MODEL EVALUATION

- Several different classifiers;
- **Nested 5-fold cross-validation:** (Inner and outer loops);
- **Stratified sampling** to ensure balanced classes.

Model	WCTF-IDF		Word2Vec	
	Accuracy	**Weighted F1-score**	**Accuracy**	**Weighted F1-score**
Random Forest	0.882 ± 0.008	0.879 ± 0.008	0.848 ± 0.011	0.848 ± 0.012
Logistic Regression	$\mathbf{0.903 \pm 0.007}$	$\mathbf{0.903 \pm 0.007}$	0.839 ± 0.012	0.847 ± 0.010
Linear SVM	0.901 ± 0.008	0.901 ± 0.008	0.851 ± 0.011	0.855 ± 0.010
XGBoost	0.896 ± 0.009	0.893 ± 0.009	0.859 ± 0.010	0.858 ± 0.011
Bagging	0.826 ± 0.013	0.831 ± 0.010	0.831 ± 0.014	0.831 ± 0.015
Decision Tree	0.795 ± 0.013	0.798 ± 0.011	0.721 ± 0.004	0.724 ± 0.004
KNN	0.679 ± 0.007	0.704 ± 0.008	0.771 ± 0.003	0.785 ± 0.005
MultinomialNB	0.856 ± 0.017	0.856 ± 0.016	—	—

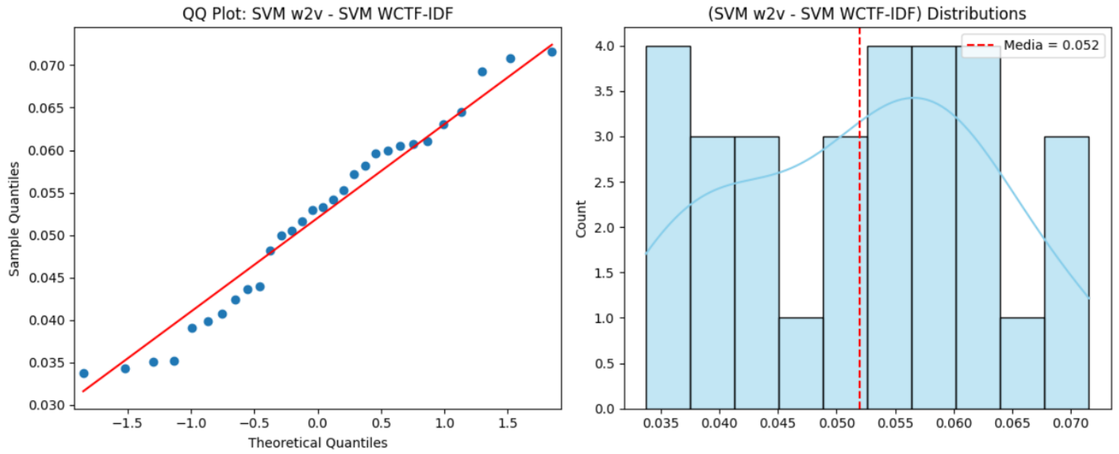
MODEL SELECTION

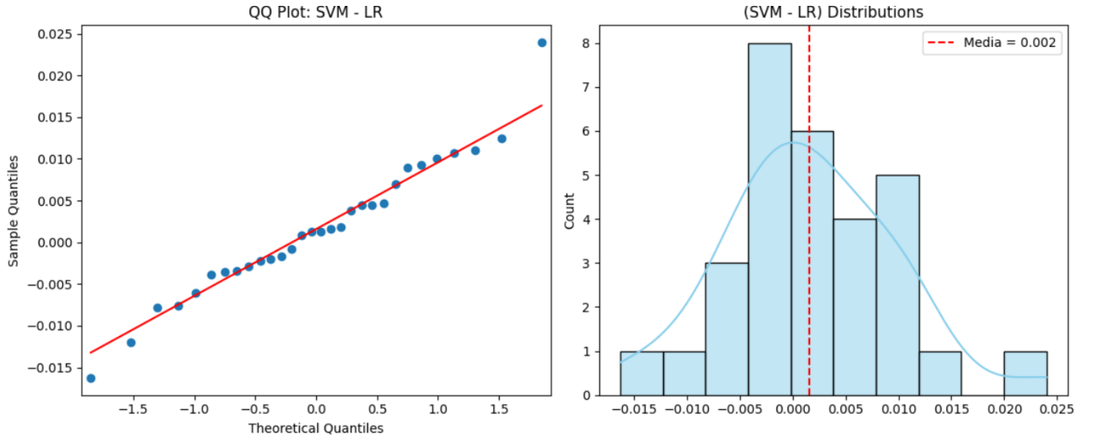
- SVM WCTF-IDF vs SVM word2vec (Wilcoxon Test)

p-value = 0.0000000019 → Statistical evidence of difference.

- SVM WCTF-IDF vs LR WCTF-IDF (Wilcoxon Test)

p-value = 0.36 → No statistical evidence of difference.

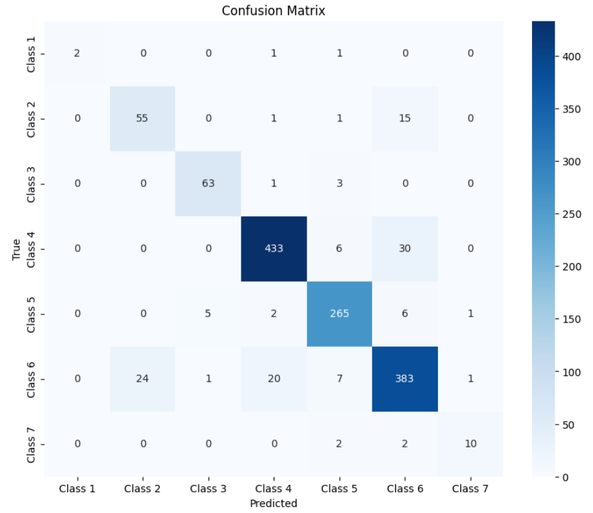




PERFORMANCE EVALUATION (Test set)

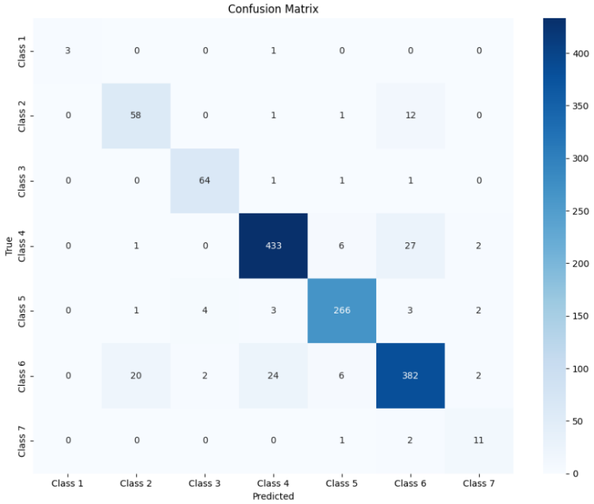
- SVM

Class	Precision	Recall	F1-Score	Support
Class 1	1.00	0.50	0.67	4
Class 2	0.70	0.76	0.73	72
Class 3	0.93	0.94	0.93	67
Class 4	0.95	0.92	0.93	469
Class 5	0.93	0.95	0.94	279
Class 6	0.88	0.88	0.88	436
Class 7	0.83	0.71	0.77	14
Accuracy		0.90		1341
Macro Average	0.89	0.81	0.83	1341
Weighted Average	0.90	0.90	0.90	1341



- Logistic Regression

Class	Precision	Recall	F1-Score	Support
Class 1	1.00	0.75	0.86	4
Class 2	0.72	0.81	0.76	72
Class 3	0.91	0.96	0.93	67
Class 4	0.94	0.92	0.93	469
Class 5	0.95	0.95	0.95	279
Class 6	0.89	0.88	0.89	436
Class 7	0.65	0.79	0.71	14
Accuracy		0.91		1341
Macro avg	0.87	0.86	0.86	1341
Weighted avg	0.91	0.91	0.91	1341



COMPARISON WITH OTHER STUDIES

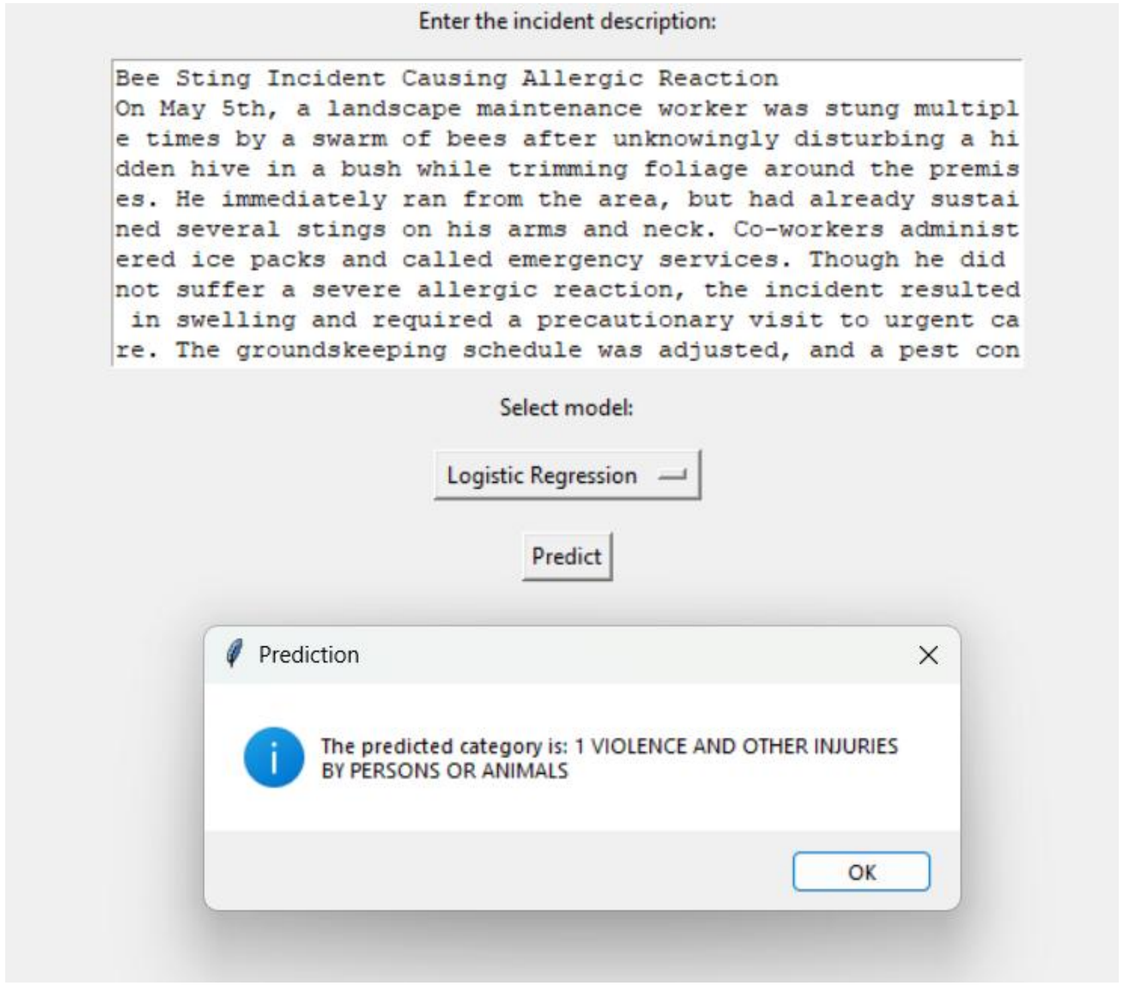
Reference paper results[2]:

- Best model: **SVM** with **8,423 features** (vs. **1,000 features** in our case);

- Overall **Accuracy** and **Weighted F1-score** around **0.91** (same as our best model);

- Class-wise F1-score for the most imbalanced classes (1 and 7):
  Paper: 0.40 and 0.62
  Our best results: **0.86** and **0.77**

INTERFACE


Enter the incident description:
Bee Sting Incident Causing Allergic Reaction
On May 5th, a landscape maintenance worker was stung multipl
e times by a swarm of bees after unknowingly disturbing a hi
dden hive in a bush while trimming foliage around the premis
es. He immediately ran from the area, but had already sustai
ned several stings on his arms and neck. Co-workers administ
ered ice packs and called emergency services. Though he did
not suffer a severe allergic reaction, the incident resulted
in swelling and required a precautionary visit to urgent ca
re. The groundskeeping schedule was adjusted, and a pest con
Select model:
Logistic Regression
Predict
Prediction
The predicted category is: 1 VIOLENCE AND OTHER INJURIES
BY PERSONS OR ANIMALS
OK

REFERENCES

[1] Cheng, M. Y., Kusoemo, D., & Gosno, R. A. (2020). Text mining-based construction site accident classification using hybrid supervised machine learning. Automation in Construction, 118, 103265.

[2] Qiao, J., Wang, C., Guan, S., & Liu, S. (2022). Construction-accident narrative classification using shallow and deep learning. Journal of Construction Engineering and Management, 148(9).

[3] Deepwiz AI. (2023). How to correctly use TF-IDF with imbalanced data. Retrieved from https://www.deepwizai.com/projects/ how-to-correctly-use-tf-idf-with-imbalanced-data

THANK YOU FOR YOUR ATTENTION