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Indian Sign Language Recognition: Support Vector Machine Approach

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Abstract

Indian Sign Language (ISL) is the primary form of communication for the dumb and deaf community in India. Recognizing Indian Sign Language plays an imperative part in promoting communication rights, social inclusion and equality for deaf people, while also contributing to technological advancement and cultural diversity. System's ability to automatically recognize ISL signs could significantly improve community interactions between deaf and people with hearing loss. The objective of this research is to design a system that can accurately recognize and interpret Indian Sign language (ISL), thereby improving communication accessibility for the deaf and dumb community. Also, enhance the accuracy of Indian Sign language (ISL) recognition. In this research, Machine Learning approach for Sign Language (SL) Recognition using Support Vector Machine (SVM) is implemented. The Support Vector Machine (SVM) model was trained using a linear kernel and a regularization parameter (C) set to 0.999 on a dataset of sequences for gesture recognition. After training, the model achieved a test accuracy of 86% on the test data. The development and implementation of gesture recognition system can increase awareness of the communication needs and rights of deaf people.

Keywords: Data preprocessing, Feature extraction, Feature selection, Sign language recognition, Machine learning algorithms, Support vector machines.

1. Introduction

Indian Sign Language (ISL) provides an essential means of communication for the deaf and hearing loss community in India. With its rich vocabulary and grammar, ISL plays an important part in facilitating interpersonal interaction, education and cultural expression of the deaf. However, effectively recognizing and interpreting ISL gestures poses significant challenges, especially in technology applications aimed at improving accessibility and inclusion of the deaf community. In recent years, use of machine learning, deep learning and AI techniques have led to significant advances in sign language (SL) recognition systems. In the study by Luqman [1], an efficient two-stream network for isolated sign language (SL) recognition was proposed, which uses accumulated video motion to effectively capture spatio-temporal information. Hierarchical sign learning module, including dynamic motion network (DMN), accumulative motion network (AMN), and sign recognition network (SRN), as well as techniques to extract key poses and expressions represents static and dynamic information of sign gestures, demonstrating superior performance in recognizing static signs. This approach outperforms other techniques by 15% in signer-independent mode on the KArSL-190 dataset and outperforms state-of-the-art techniques on the LSA64 dataset, demonstrating its effectiveness in sign language recognition. In study by Chandwani's [2], study focused on using Mediapipe hand tracking technique and support vector machine (SVM) model to recognize static sign gestures related to sign language gestures as alphabets and frequently used words. The study by Katoch et al. [3], presents a novel approach to Indian Sign Language (ISL) recognition by integrating Speeded-Up Robust Features (SURF) with Support Vector Machine and Convolutional Neural Network (CNN) algorithms. This research delves into the mathematical underpinnings of SVM, demonstrating its efficacy combined with image processing techniques like SURF to recognize sign language. Wanyu Zhang's paper [4], significantly contributes to sign language (SL) recognition through deep image processing. The proposed method focuses on feature extraction based on the wrist joint. It also explains how to track wrist joint positions from depth images and how to train machine learning models (e.g. SVM, CNN) for recognition. The achieved recognition rate of 91.3 proves the effectiveness of the proposed method. The challenges in Sign language recognition involve a wide range of gestures, each with variations due to individual signing styles, regional differences and context. Sign language is inherently dynamic, involving continuous motion and temporal patterns. Capturing spatio-temporal information effectively is crucial. Sign language recognition models should generalize well to unseen signs or variations not present in the training data. Handling novel signs is a challenge. To overcome these challenges, this initiative aims to provide a system that improves the performance and recognition accuracy. The main objective of the method proposed is to develop an SVM based model for Indian Sign Language (ISL) recognition and build an effective model to improve the recognition accuracy.

The summary of the paper is presented as follows: An overview of related research in the area of Indian sign language (SL) recognition is discussed in Section 2. The methodology used for the study is described in Section 3, Section 4 presents the experimental setup, Section 5 explains the results, while Section 6 explains the conclusion and future scope.

2. Related Work

In [5], they developed a system which recognizes hand gestures corresponding to the English alphabet in Indian Sign Language (ISL) and translates them into Braille Script in real time. The proposed mechanism identifies 26 hand poses representing the 26 letters of the English alphabet according to ISL. Hand signs are captured by a camera, and their frames are used for identification. Convolutional Neural Network (CNN) is used to recognize hand gestures. Lookup maps Braille Script translation easy. The proposed method achieves an impressive accuracy of 94.23% on the Sign-Language-Custom (SLC) model. The authors [6], have used computer vision, machine learning, and deep learning methods to recognize ISL. The process involves a series of pre-processing steps on the captured image, which includes various Computer Vision techniques such as conversion to gray-scale and thresholding using the OTSU algorithm. The author used Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and pre-trained models, VGG-19 and Inception-V3 using Transfer Learning mechanism to train the system. Tyagi et.al. in [7], a hybrid FAST-SIFT-

CNN (HFSC) method is proposed for vision-based Indian Sign Language (ISL) recognition. The HFSC model is trained on standard benchmark datasets, including MNIST, Jochen-Trisech, and NUS hand posture-II. Its performance is compared with existing sign language recognition approaches. On a uniform dataset, the HFSC algorithm achieved an impressive accuracy of 97.89%. Even on complex backgrounds, the HFSC maintains an equivalent accuracy of 95%. In the study by Athira et al. [8], the researchers focused on developing a sign language recognition system that is independent of removing co-articulations from live videos. This research is relevant to the task of sign language recognition using Support Vector Machines (SVM) because it addresses the challenges of accurately recognizing sign language gestures, even in live video scenarios. Next, this is important for developing a robust sign language recognition system. The authors [9], the system includes an Android application that translates Indian sign language gestures to English using vision processing and audio output. This approach reduces latency and accurately recognizes one-handed sign representations of the numbers 0 to 9. In [10], the authors proposed a vision-based hand gesture recognition system for ISL using a convolutional neural network (CNN). The proposed system achieved an impressive recognition accuracy of 93.5% on the test dataset.

In [11], they proposed a system to record hand movements using a webcam. The resulting image go through many processing stages, including grayscale conversion, dilatation, and masking. The model is trained with a convolutional neural network (CNN). The system predicts and displays the name of the sign captured in real time. In [12], the author proposed two recognition models in Indian Sign Language (ISL). Model I was trained with one dominant hand, while model II was trained with both hands. The authors report that Model II can accurately predict signs, regardless of the signer's hand, recognizing both alphabets and numbers in ISL. The authors use key points and transfer learning techniques in their approach, which allows training models quickly. They claim to have achieved 99% validation accuracy, suggesting that their method has a high level of effectiveness. In [13], the authors used the three-step method a contour matching approach, Local features such as gradient descriptors and keypoints are extracted using HOG, SIFT, SURF, LBP, FAST. Feature fusion is achieved by concatenating features from HOG with LBP, SIFT with FAST, BOVW model with SURF, Random Forest, SVM, Logistic regression, Naïve Bayes trained on a large datasets and experimented tuning of hyperparameters. The study demonstrates that their model consistently achieves an outstanding accuracy rate of 100 when using feature fusion techniques. The research by Kothadiya et al. [14], presented SIGNFORMER, a DeepVision Transformer model designed for sign language (SL) recognition, suitable for the task of sign language recognition using machine learning techniques such as support vector support (SVM). In [15], the authors used a three-step resizing and contours extraction method. Fourier descriptors are used for frequency domain analysis and gray level co-occurrence matrix for spatial domain analysis and various machine learning models including SVM, Logistic Regression, Random Forest, K-Nearest Neighbor and Naive Bayes, trained on a standard dataset. Among the tested classifiers, K-Nearest Neighbors demonstrated the highest accuracy, reaching 99.82%. To validate the robustness of their approach, they used k-fold cross-validation with 5 folds. In [16], the research covers various classification models, from distance metrics to kernel-based approaches and feed-forward neural networks, as well as Deep Learning-based methods like CNN, LSTM, GAN and transformer. Table 1 summarizes various studies of Indian Sign Language recognition and their respective limitations.

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Table 1: Comparative study with sign recognition approaches

Reference	Authors	Paper Title	Limitations
[5]	Shubham Tiwari, Yash Sethia, Ashwani Tanwar, Harsh Kumar, Rudresh Dwivedi	An Approach to Real-Time Indian Sign Language Recognition and Braille Script Translation	Recognizing individual letters of the English alphabet in ISL; not considering words, phrases, and contextual variations
[6]	Niranjan Panigrahi	Artificial Intelligence based Indian Sign Language Recognition with Accelerated Performance under HPC Environment	Lack of implementation of Object detection techniques, facial expressions
[7]	Tyagi, Akansha and Sandhya Bansal	Hybrid FAST-SIFT-CNN (HFSC) approach for Vision-Based Indian Sign Language Recognition	Accuracy on complex backgrounds; more extensive evaluation on diverse backgrounds needed
[8]	P.K. Athira, C.J. Sruthi, A. Lijiya	A Signer Independent Sign Language Recognition with Co-articulation Elimination from Live Videos: An Indian Scenario	Recognizing more complex and dynamic gestures involving both hands or facial expressions
[9]	D. Karthika Renuka, L. Ashok Kumar	Indian Sign Language Recognition Using Deep Learning Techniques	Handling sentence-level context and understanding nuances in sign language grammar remains an open research area
[10]	Boinpally Ashwanth, Sri Bhargav Ventrapragada, Shradha Reddy Prodduturi, Jeshwanth Reddy Depa, K. Venkatesh Sharma	Vision-based Hand Gesture Recognition for Indian Sign Language Using Convolution Neural Network	Focused primarily on single-handed sign representations; not considering two-handed gestures, facial expressions, and body movements
[11]	Mallikharjuna Rao K, Harleen Kaur, Sanjam Kaur Bedi, M A Lekhana	Image-based Indian Sign Language Recognition: A Practical Review using Deep Neural Networks	Lacks details on system latency and computational efficiency
[12]	Shilpa N. Ingoley, Dr. Jagdish W. Bakal	Use of Key Points and Transfer Learning Techniques in Recognition of Handedness Indian Sign Language	Dynamic signs not considered
[13]	B V Poornima, S Srinath,	Performance Evaluation of	Generalizability of results to

Reference	Authors	Paper Title	Limitations
	S Rashmi, R Rakshitha	Feature Fusion Approaches for Indian Sign Language Recognition System	complex backgrounds or a wider range of signs not considered
[14]	Deep R. Kothadiya, Chintan M. Bhatt, Tanzila Saba, Amjad Rehman, Saeed Ali Bahaj	SIGNFORMER: DeepVision Transformer for Sign Language Recognition	Dynamic or continuous sign language not addressed, lacking real-time recognition
[15]	B V Poornima, S Srinath	Frequency and Spatial Domain-Based Approaches for Recognition of Indian Sign Language Gestures	Spatial domain features demonstrated good performance but fall short in extracting crucial dominant features in ISL gestures
[16]	Attili SubhaVidisha, Anubuthi Kottapalli, Anshula Aithal, Amanpreet Kaur Pawa, Ashwini M Joshi	Analysis of Vision-based Techniques for the Translation of Indian Sign Language	Semantic relations between multiple words not addressed

3. System Architecture

This section explains about methodology used in implementing system. The methodology shows how Indian sign language is recognized using machine learning techniques. Figure 1 describes the process from input data to accuracy assessment, including image acquisition, hand landmark detection, preprocessing, dataset splitting, training SVM model with linear kernel and C parameter, model validation and testing, and calculating accuracy.

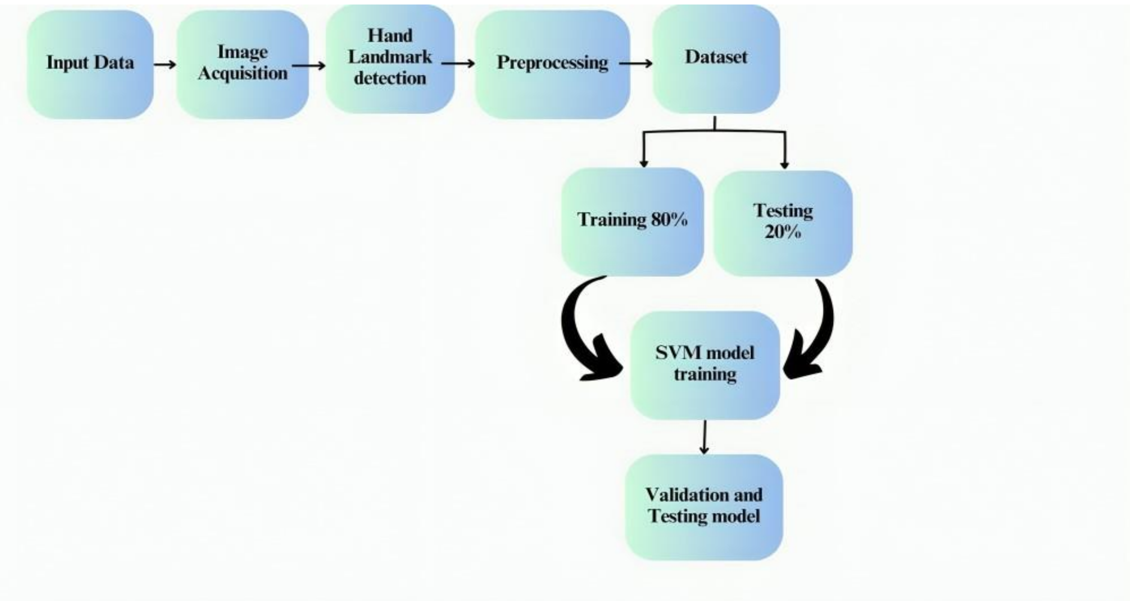

Figure 1. Overview of system

Steps involved in system overview are:

3.1 Input Data: This step involves obtaining the raw data, which can be images or videos containing sign language gestures. The data includes various gestures performed by individuals, recorded by camera.

3.2 Image Acquisition: Images or frames are captured from the input data. These images contain hand gestures or sign language expressions. Frame extraction from videos is used.

3.3 Hand Landmark Detection: This involves identifying key points or landmarks on the hand within the captured image. These key points include the fingertips, knuckles, and palm landmarks. Hand landmarks were extracted from images using MediaPipe.

3.4 Preprocessing: Preprocessing steps are applied to the detected hand landmarks to prepare them for further analysis. This includes normalization, scaling, or feature extraction, data augmentation, and dimensionality reduction.

Figure 2. Preprocessing steps

3.5 Split the Dataset: The preprocessed data is divided into: the train set and the test set. Typically, a certain percentage of the data (e.g., 80%) is used to train, and the remaining data (e.g., 20%) is used for testing. The split ensures that the performance of model can be evaluated on unseen data.

3.6 Training SVM model with Linear Kernel and C parameter: In this step, the Support Vector Machine (SVM) is trained using the training data. The SVM model is configured to use a linear kernel and the parameter C is specified for regularization. The training process involves finding the optimal decision boundary to separate different classes of hand gestures.

3.7 Model Validation and Testing: After training, the SVM model is validated and tested using the test data. Validation ensures that the model's performance is evaluated on a separate dataset to avoid overfitting. Testing involves predicting the labels of the test data using the trained model.

3.8 Accuracy evaluation: The accuracy of the SVM model is evaluated by comparing the predicted labels with the ground truth labels. The ratio of correct predictions to the total number of predictions used to calculate accuracy. An overview of the model's hand gestures recognition performance is given in this step.

4. Experimental Setup

This section explains implementation of this research, algorithm steps and mathematical model of proposed system.

4.1 Algorithm: steps involved are

1. Import Libraries: Import necessary libraries including numpy, sklearn, and matplotlib.

2. Load Data: Load the training data from the train_data. pickle file.

3. Preprocess Data: Define max_sequence_length for padding sequences.

- pad or truncate sequences to max_sequence_length
- convert sequences to numpy array
- extract labels from data dictionary

4. Split Data: Split the preprocessed data into train and test sets using train_test_split ().

5. Reshape Data: Reshape the data to fit the input shape required by the SVM model.

6. Train SVM Model: Create an SVM model with a linear kernel and a regularization parameter C. Train the SVM model using the training data.

7. Test Model: Use the trained model to make predictions on the testing data.

8. Evaluate Model: Calculate the accuracy score to evaluate the model's performance.

4.2 Mathematical Model

A mathematical model describes a system using mathematical concepts and language. Mathematical model for proposed system is shown below:

● **Load Data**: Let, D represent the loaded data, which consists of sequences and their corresponding labels.

$$D = \{(x_i, y_i)\}_{i=1}^{N} \quad (1)$$

Where, xi represents a sequence and yi represents its label.

● **Preprocess Data**: Let, Pad (x, L) represent the padding function, which pads sequence x to length L. Let, Truncate (x, L) represent the truncation function, which truncates sequence x to length L. Then the preprocessed data ′D′ is obtained as follows:

$$D' = \{(\mathrm{Pad}(\mathrm{Truncate}(x_i, L), L), y_i)\}_{i=1}^{N} \quad (2)$$

● **Split Data**: Let, Dtrain and Dtest represent the train and test datasets, respectively. We split the data into training and testing sets:

$$D_{\mathrm{train}}, D_{\mathrm{test}} = \mathrm{Split}(D, \mathrm{test\_size}) \quad (3)$$

● **Reshape Data**: Let, reshape (x) represent the function that reshapes sequence x into a vector. Then, the reshaped training and testing datasets Xtrain and Xtest are obtained as follows:

$$X_{\text{train}} = \{\text{Reshape}(x_i)\}_{i=1}^{M}$$
$$X_{\text{test}} = \{\text{Reshape}(x_i)\}_{i=1}^{L} \quad (4)$$

Where, M and L are the sizes of the training and testing sets, respectively.

● **Train SVM Model**: We train an SVM model svm_model using the training data Xtrain and labels ytrain

$$\text{svm\_model} = \text{TrainSVM}(X_{\text{train}}, y_{\text{train}}) \quad (5)$$

● **Test Model**: We use the trained SVM model to predict labels for the testing data Xtest.

$$\hat{y}_{\text{test}} = \text{Predict}(\text{svm\_model}, X_{\text{test}}) \quad (6)$$

● **Evaluate Model**: To assess the SVM model's performance, we compute the accuracy score.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

(7) This mathematical model represents the workflow and operations involved in the proposed system to recognize hand gestures using mathematical notation and functions.

5. Experimental Results

The algorithm has been implemented on Python Jupyter notebook. The dataset is divided into two sets. The training set consists of 80% of the total data and the remaining 20% is used as test data. The main objective of the performance analysis of methodology used is to maximize the accuracy of the model. As no standard dataset available for ISL alphabets in Marathi we have created our own dataset with sample size of 3120 samples with sequence length of 3900 features on training and 780 samples with sequence length of 3900 features on test data as shown in figure 3.

Figure 3. Sample images from dataset

The system is trained to recognize 42 alphabets in Marathi. Current results are promising, keeping in mind that few improvements could provide better results. For evaluation of model following performance metrics are considered:

1. Accuracy

It is defined as the percentage ratio of correctly classified gestures to the total number of gestures in a particular class during the testing phase. It is calculated using equation (7).

2. Precision

Precision is the ratio of true positive predictions to the total number of positive predictions made by

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the classifier. It measures the accuracy of positive predictions and is calculated as follows:

Precision=True Positives/(True Positives + False Positives) (8)

3. Recall

Recall rate is the ratio of true positive predictions to the total number of actual positive instances in the dataset. It measures the classifier's ability to find all the relevant cases within the dataset and is calculated as follows:

Recall=True Positives / (True Positives + False Negatives) (9)

4. F1-score

F1-score is the harmonic mean of precision and recall. The F1-score achieve its best value at 1 (perfect precision and recall) and worst at 0. It provides a balance between precision and recall and is computed as:

F1-score=2× (Precision × Recall / Precision + Recall) (10)

5. Confusion matrix

A confusion matrix is a table that is commonly used to describe the performances of a classification model on a test data set with known real values. It allows to visualize the performance of an algorithm by showing the number of true positive, true negative, false positive, and false negative predictions made by the classifier. The classes as per Devnagari signs shown in figure 4. The classification evaluation metrics for multiple classes is shown in table 2 and confusion matrix from testing data is shown in figure 5. This figure shows that the color of the diagonal line is dark and has higher values, indicating that many predictions are correct. As shown in table 3, the proposed result is compared with the method used in existing systems. The accuracy of the proposed system is more than the existing system.

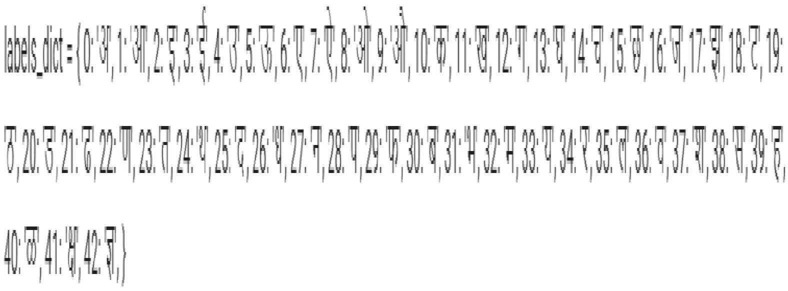

Figure 4. Classes as per Devnagari signs

Table 2: Classification evaluation metrics

Class	Precision	Recall	F1-Score	Support
0	0.68	1.00	0.81	50
1	1.00	1.00	1.00	50
2	1.00	1.00	1.00	50
3	1.00	1.00	1.00	50
4	1.00	0.96	0.98	50

5	1.00	1.00	1.00	50
6	1.00	1.00	1.00	50
7	1.00	1.00	1.00	50
8	0.98	1.00	0.99	50
9	1.00	0.94	0.97	31
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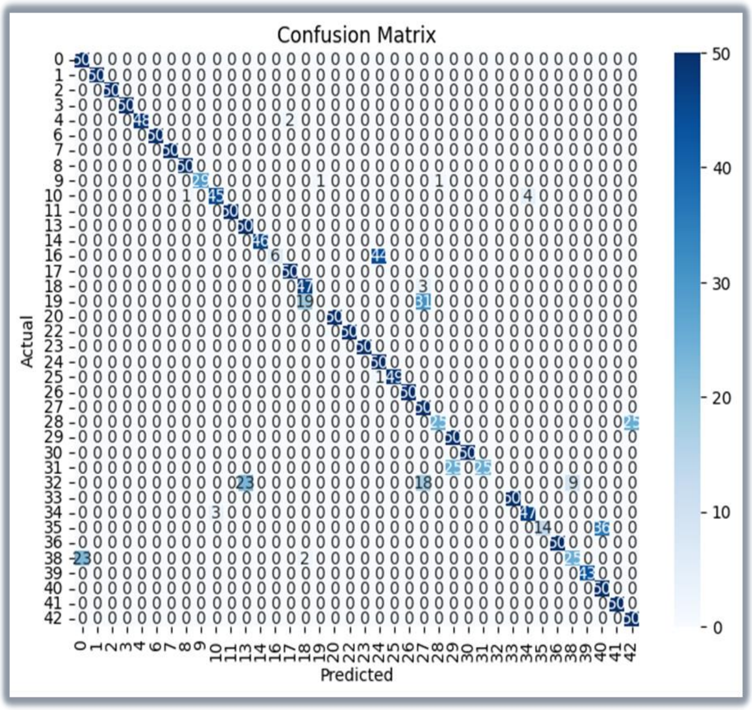

Figure 5. Confusion matrix

Table 3: Comparative performance evaluation with existing approaches

Year	Reference	Method	Accuracy
2015	[17]	Latent SVM (HOG + OP + Kinect)	82.9%
2016	[18]	Decision tree classifier	82%
2017	[19]	Deep convolutional network (DCNN)	80%
2021	[20]	InceptionV3 CNN with transfer learning	85%
2022	[21]	YOLOv3 CNN with darknet-53 backbone	82%
2023	[22]	You Only Look Once-Neural Architecture Search	86%
	Proposed model	SVM-based	86%

6. Conclusion and Future Scope

The Indian sign Language recognition system helps deaf individuals and normal people communicate more effectively. In this study, we attempted to develop support vector machine-based model. Some classes are well-classified by the model with accuracy of 86%. Further analysis, including examining misclassified samples and potentially refining the model, may be necessary to improve overall classification performance. Future work can be extended to address issues such as imbalanced data could help improve the model's performance on low-support classes.

Conflicts of Interest

The authors have no conflicts of interest to declare

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