ENHANCING ACCURACY IN OBJECT TRACKING USING NOVEL YOLO COMPARED WITH K-NEAREST NEIGHBOUR

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Article History: Received: 12.12.2022 **Revised:** 29.01.2023 **Accepted:** 15.03.2023

Abstract

Aim: To detect the accuracy in object tracking using the K-Nearest Neighbour algorithm.
Materials and Methods: This study contains 2 groups i.e.intervention YOLO algorithm and comparison K-Nearest Neighbour algorithm.Each group has a sample size of ten people, and the study parameters are alpha = 0.05, beta = 0.2, and power = 0.8.Their accuracies are also compared to one another using different sample sizes. **Results:** The Novel Yolo is 92.8370 more accurate than the K-Nearest Neighbour of 87.64% in Fake Review Detection.
Conclusion: The Yolo model is significantly better than the LR in identifying Fake Review. It can be also considered as a better option for Fake News detection.

Keywords: Object tracking, Deep learning, Frame, Novel yolo, K-Nearest Neighbour, Real time tracking, Detection.

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1. Introduction

The use of computer vision to recognize and track moving objects is commonly used to examine manufacturing items, monitor traffic flow, and detect legal violations (Zhang, Fan, and Ming 2022). Detecting moving objects may be done using optical flow, frame difference technique, and background difference method (Mariam et al. 2022). However, most approaches for tracking moving objects require the usage of models and matches of nearby video frames, which not only increases the complexity of the calculation process but also makes real-time object tracking problematic(Spriet et al. 2022). Compressed sensing extracts information from tiny bits of data, reducing the amount of processing space required to track things (Faraz et al. 2022).

As a result, it's commonly used for real-time tracking of moving objects. However, the tracking algorithm based on compressed sensing still has issues such as using a large number of video frames, being insensitive to fast-moving objects, and not having enough background information to the model, all of which cause the algorithm's performance to fall short of the requirements (Challa 2011). The research provides an improved real-time tracking method based on comprehensive sensing to address the issues (Han et al. 2014; Hua et al., n.d.). The technique extracts features in the compressed domain using compressed sensing characteristics, ensuring that the track is tracked in real-time (Xing et al. 2021). The K-Nearest Neighbour classifier, on the other hand, is used to distinguish things from their surroundings. The results of the experiments show that the algorithm is capable of increasing track accuracy(Mazzeo, Ramakrishnan, and Spagnolo 2019).Our institution is passionate about high quality evidence based research and has excelled in various domains (Vickram et al. 2022; Bharathiraja et al. 2022; Kale et al. 2022; Sumathy et al. 2022; Thanigaivel et al. 2022; Ram et al. 2022; Jothi et al. 2022; Anupong et al. 2022; Yaashikaa, Keerthana Devi, and Senthil Kumar 2022; Palanisamy et al. 2022).

Real time tracking is the process of locating moving objects over time using the camera in video sequences in real time. The objective of object tracking is to associate target objects in Real time tracking consecutive video frames. Object tracking requires location and shape or features of objects in the video frames.Real time tracking using deep learning method. The accomplishments of real-time tracking are discussed in the second part. The notion of compressed sensing and the K-Nearest Neighbour classifier is introduced in the third part. The algorithm is presented in full in the fourth part(Faraz et al. 2022; Zhang, Fan, and Ming 2022). The experiments in the fifth part verify the algorithm. Finally, the conclusion is reached.(Betke and Wu 2016). By learning the motion of an object offline, GOTURN revolutionised the way we apply Deep Learning to the challenge of tracking. The GOTURN model has been trained on hundreds of video sequences and does not require any runtime learning. As a result, many real-time trackers use online learning algorithms, which are often significantly quicker than deep learning.

2. Materials and Methods

Research work was carried out at Machine learning, Saveetha Institute of Medical and Technical Science. The study consists of two sample groups i.e Novel Yolo and K-Nearest neighbour. Each group consists of 10 samples with a pre-test power of 0.363. The sample size 10 kept the threshold at 0.05, G power of 80%, confidence interval at 95%, and enrolment ratio as 1. The dataset used for classification is taken from the Kaggle Inc. Database, an open-source data repository for Fake Review Detection using various machine learning techniques.

K-Nearest Neighbour Classifier

K-Nearest Neighbour (K-Nearest Neighbour) is a non-parametric approach for classification and regression in pattern recognition. The K-Nearest Neighbour classification is used to categorise K = 1 as the single closest neighbour, and the K-Nearest Neighbour regression is used to get the average values of K nearest neighbours. The goal of this regression is to find a functional description of the data. The K-Nearest Neighbour classifier is a simple and fundamental data distribution algorithm [2], [6] that is used to categorise frame objects in the feature space based on closets. K-Nearest Neighbour is a lazy learner that stores training datasets and assigns query similarity between test data and training set records that must be determined in order to forecast the test data class. The majority of k-nearest neighbours in the training data set to indicate the class. When K = 1, the simplest version of the K-Nearest Neighbour is the Nearest Neighbour (NN) rule. In this approach, each sample is categorised in relation to its immediate surroundings, and if the classification of a sample is unknown, it may be predicted by looking at the classification of its closest neighbours. The distance between the unknown sample and all of the samples in the training set may be determined, and the sample in the training set closest to the unknown sample corresponds to the sample in the training set with the smallest distance. As a result, the categorization of the unknown sample can be based on the classification of its nearest neighbour. In general, a decision rule

is a function that informs you what to do in any situation. The K-Nearest Neighbour decision rule is depicted in Figure 1 below, with a collection of samples categorised frame into two classes. Figure 1(a) demonstrates how the K-Nearest Neighbour decision rule for K = 1 classifies an unknown sample using just one known sample, whereas Figure 1(b) shows how the K-Nearest Neighbour decision rule for K = 4 classifies an unknown sample using several known samples.
The choice of K, as well as the distance measure used, affects the effectiveness of a K-Nearest Neighbour classifier [20–25]. Because the radius of the local area is defined by the distance of the Kth nearest neighbour to the query, and because K provides various conditional class probabilities, the sensitivity of the neighbourhood size K selection affects the estimate. Because of the data sparsity and the noisy, unclear, or mislabeled points, the local estimate tends to be very bad if K is very small. To address the issue, relevant research has been conducted in order to improve K-Nearest Neighbour's classification performance. The selection of a proper neighbourhood size (K) is the most important problem in K-Nearest Neighbour. In the case of the K-Nearest Neighbour, the short training sample size can have a significant impact on the selection of the best candidate.

Quality of K-Nearest Neighbour

The accuracy of our data model's predictions is measured by the K-Nearest Neighbour classifier's quality. Validation of the data sets is required for this. Validation is the process of determining if numerical findings describing hypothesised connections between variables are acceptable as data descriptions. We must test any machine learning model with previously unknown data in order to assess its performance.

STATISTICAL ANALYSIS

The minimum requirement to run the software used here is intel core I3 dual core CPU@3.2 GHz, 4GB RAM, 64 bit OS, 1TB hard disk space personal computer and software specification includes Windows 8, 10, 11, Python 3.8 and MS-Office. Statistical package for the social sciences version 26 software tool was used for statistical analysis. An independent sample T-test was conducted for accuracy. Standard deviation, standard mean errors were also calculated using the SPSS software tool. The significance values of proposed and existing algorithms contain group statistical values of proposed and existing algorithms.

3. Result

For single object target prediction and subsequently end-to-end multiple object tracking, we examined the performance of Kalman filters, K-Nearest Neighbors, and LSTMs. For the purpose, we have provided the groundwork for a single target prediction challenge. We compare our truth coordinates in each frame. predictions based on the annotated ground truth by humans.LSTMs outperform other approaches by a factor of ten2 x. The error is calculated using the distance between two points. The target's expected coordinate and the actual ground truth measurement.

4. Discussion

While K-Nearest Neighbour was utilised as a starting point, it showed a number of important aspects of the data. The mean squared error of the K-Nearest Neighbour depends on the number of films used for training. This demonstrates that there are a number of fairly typical patterns that are effectively caught throughout the course of five recordings. The pace of progress, however, rapidly slows and the line flattens out. This shows that the majority of the new patterns seen are rare and unsuitable for prediction.
It's also worth mentioning that K-Nearest Neighbour was significantly slower than the other techniques during testing. Depicts the trajectory of a single item through time as well as the predictions provided by each of the approaches under consideration. Although this is only one example, it demonstrates how effectively each method monitors the object. Take note of how forecasts overshoot when the object rotates, and how it may take some time to adjust to the new trajectory.

5. Conclusion

The research provides a better method based on the difficulties of the compressed sensing approach. An algorithm for real-time tracking based on compressed data sensing. The program takes advantage of compressed sensing. It considerably decreases the amount of computing space required. To categorise frame objects and the backdrop, the program employs a K-Nearest Neighbour classifier. The K-Nearest Neighbour classifier is used to categorise frame objects and enhance the tracking performance of moving objects. Object tracking using the K-Nearest Neighbour classifier is proposed in this study. The K-Nearest Neighbour classifier is used to distinguish between the target and background of an image, and it produces accurate results for real-time object tracking. This approach allows for real-time object tracking, which enhances the tracking effect.

Declarations

Author Contributions

Author PR was involved in data collection, data analysis, data extraction, manuscript writing. Author AJ was involved in conceptualization, data validation, and critical review of the manuscript.

Acknowledgment

The authors would like to express their gratitude towards Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (Formerly known as Saveetha University) for providing the necessary infrastructure to carry out this work successfully.

Funding

We thank the following organisations for providing financial support that enabled us to complete the study.

1. Vee Eee Technologies Solution Pvt. Ltd.
2. Saveetha University.
3. Saveetha Institute of Medical and Technical Sciences.
4. Saveetha School of Engineering.

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Tables and Figures

Table 1. Pseudocode for Yolo

// I : Input dataset records
1. Import the required packages.
2. Convert the Data Sets into numerical values after the extraction feature.
3. Assign the data to X_train, Y_train, X_test and Y_test variables.
4. Using train_test_split() function, pass the training and testing variables.
5. Give test_size and the random_state as parameters for splitting the data using Yolo training.
6. Calculate the accuracy of the model.
OUTPUT: Accuracy

Table 2. Pseudocode for K - Nearest neighbour

// I : Input dataset records
1. Import the required packages.
2. Convert the Data Sets into numerical values after the extraction feature.
3. Assign the data to X_train, Y_train, X_test and Y_test variables.
4. Using train_test_split() function, pass the training and testing variables.
5. Give test_size and the random_state as parameters for splitting the data.
7. Compiling the model using metrics as accuracy.

8. Evaluate the output using X_test and Y_test function
9. Get the accuracy of the model.
OUTPUT: Accuracy

Table 3. Accuracy of Fake Review Detection using Yolo

Test size	**Accuracy**
Test 1	98.47
Test 2	97.28
Test 3	96.85
Test 4	95.28
Test 5	94.17
Test 6	93.45
Test 7	92.15
Test 8	91.64
Test 9	91.22
Test 10	90.75

Table 4. Accuracy of K - Nearest Neighbour

Test size	**Accuracy**
Test 1	87.64
Test 2	87.42
Test 3	87.11
Test 4	86.43
Test 5	86.27
Test 6	85.34
Test 7	84.38
Test 8	83.92
Test 9	82.14
Test 10	81.55

Table 5. Group, Accuracy, and Loss value uses 8 columns with 8 width data for bone age prediction.

SI.NO	**Name**	**Type**	**Width**	**Decimal**	**Columns**	**Measure**	**Role**
1	Group	Numeric	8	2	8	Nominal	Input
2	Accuracy	Numeric	8	2	8	Scale	Input
3	Loss	Numeric	8	2	8	Scale	Input

	Group	**N**	**Mean**	**Std Deviation**	**Std.Error Mean**
Accuracy	YOLO	10	92.8370	1.75647	.55545
	K-Nearest Neighbour	10	83.8140	1.87937	.59431
Loss	YOLO	10	7.1630	1.75647	.55545
	K-Nearest Neighbour	10	16.1860	1.87937	.59431

Table 6. Independent sample T-test t is performed on two groups for significance and standard error determination. the p-value is greater than 0.05 (.028) and it is considered to be statistically insignificant with a 95% confidence interval

		Levene's Test for Equality of variance		**T-Test for equality of mean**						
				t	**df**	**Sig(2-tailed)**	**Mean difference**	**Std.Error Difference**	**95% confidence of Difference**	
		F	**Sig**						**Lower**	**Upper**
Accuracy	**Equal variances assumed**	.043	.838	11.092	18	.000	9.02300	.81346	7.31398	10.73202
	Equal Variances not assumed			11.092	17.918	.000	9.02300	.81346	7.31342	10.73258
Loss	**Equal variances assumed**	.043	.838	-11.092	18	.000	- 9.02300	.81346	-10.73202	-7.31398

	Equal Variances not assumed			-11.092	17.918	.000	- 9.02300	.81346	-10.73258	-7.31342

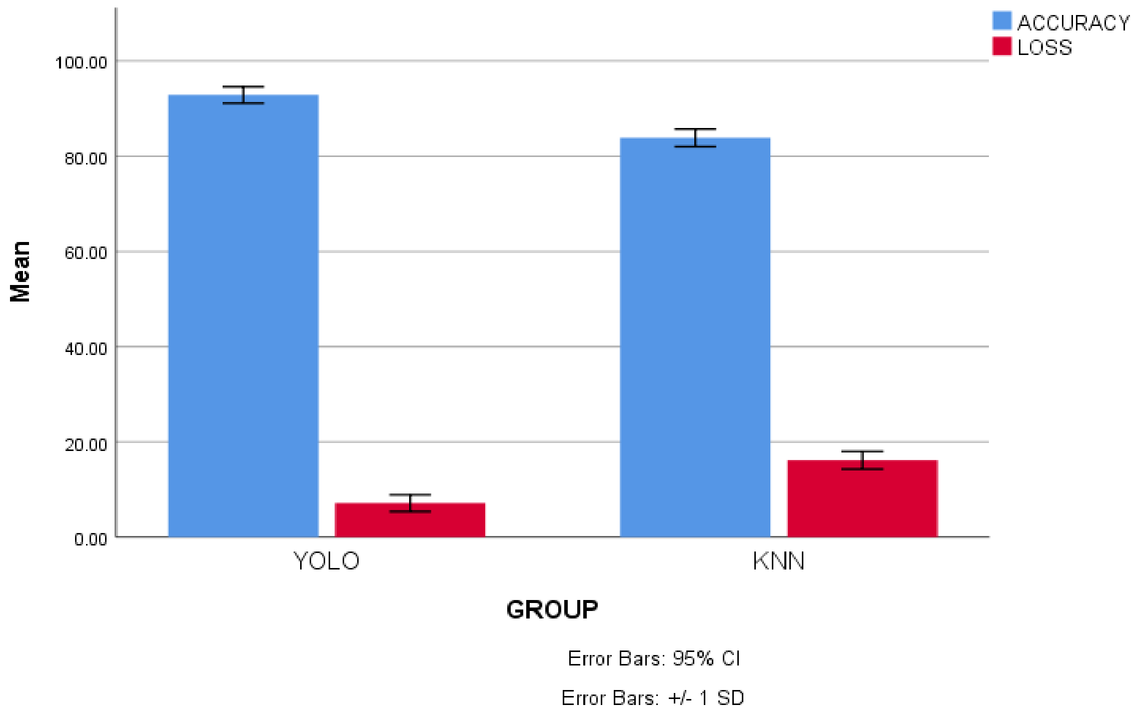

Fig. 1. Comparison of Novel YOLO and K-Nearest Neighbour in terms of mean accuracy. The mean accuracy of the YOLO is better; than the K-Nearest Neighbour. The standard deviation of the YOLO is slightly better than the K-Nearest Neighbour. X-Axis: Novel YOLO vs K-Nearest Neighbour. Y-Axis: Mean accuracy of detection ± 1 SD.