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A Truth Discovery Method with Trust-Aware Self-Supervised Model for Visual Crowdsensing

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Abstract

Crowdsensing relies on truth discovery methods to obtain reliable data. However, existing truth discovery methods for Crowd Sensing systems face challenges in effectively evaluating the quality of uploaded image data by workers and defending against attacks by malicious workers. To overcome these issues, we introduce a truth discovery method with the trust-aware self-supervised discriminative (SSD) model for visual crowdsensing, namely TASSD. In the TASSD, we incorporate the worker's trustworthiness in the re-weighting mechanism of the SSD model, thereby improving system robustness and reliability. Then, we designed a trust update method to accurately obtain the worker's trustworthiness. Experimental results demonstrate the superiority of our proposed TASSD over traditional anomaly detection methods, particularly in scenarios with high ratios of abnormal data. TASSD effectively addresses disguised malicious worker attacks that achieve high credibility.

Keywords: Visual Crowdsensing, Truth Discovery Method, Self-Supervised Discriminative Model, Trust Evaluation

1. Introduction

Mobile Crowd Sensing (MCS) (Zhou et al., 2018; Wang et al., 2018, 2021) is a technique that collects data from mobile devices to collectively sense and analyze the environment. Recently, Visual Crowdsensing (VCS) has gained popularity by utilizing the built-in cameras of smart devices to provide richer content compared to traditional MCS, such as gathering images to sense air quality (Pan et al., 2017) and detect traffic accidents (Barachi et al., 2020). However, acquiring high-quality data in MCS often requires significant time and effort, as workers need to physically move to designated locations, resulting in higher data collection costs (Cheung et al., 2015). Unfortunately, some unscrupulous workers may intentionally report low-quality or even fabricated data and collude to deceive the platform (Gong and Shroff, 2018). Therefore, it is necessary to develop relevant technologies to identify false data.

Truth discovery methods are commonly used to extract reliable information from noisy data submitted by workers (Li et al., 2014a, 2016; Zhao and Han, 2012). The methods utilize worker consistency and majority agreement to extract high-quality information from noisy data, giving more weight to trustworthy workers in the aggregation process. However, these methods struggle with unstructured data like images, as they can only detect lazy workers, not malicious ones uploading poisoned data. As shown in Figure 1, in an autonomous driving model, malicious workers may manipulate decision boundaries by uploading erroneous data, causing a traffic sign classifier to misclassify "stop" as "speed limit" during the testing phase, which could result in an autonomous vehicle continuing to steer instead of stopping to avoid obstacles (Chen et al., 2021).

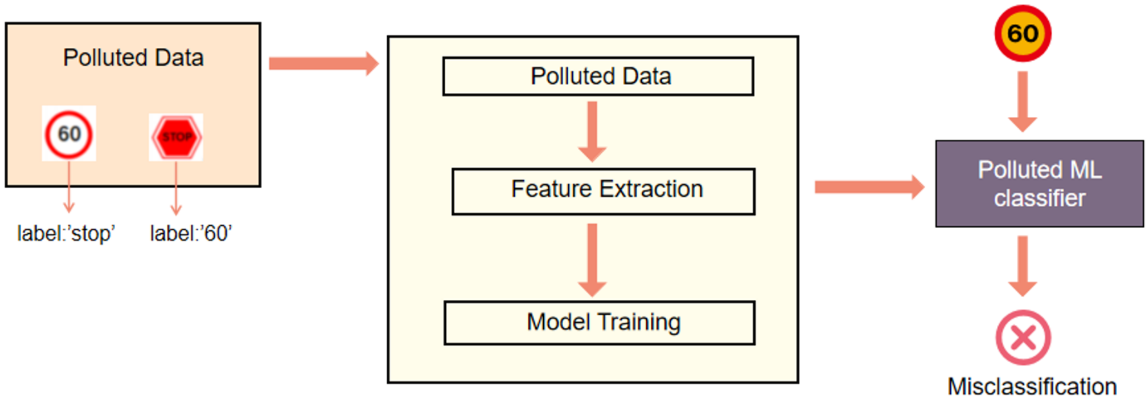

Figure 1: The impact of contaminated labeled data on model prediction accuracy.

The problem of identifying low-quality images from massive images can also be regarded as an anomaly detection problem. A representative solution for anomaly detection is self-supervised learning. For example, E^3Outlier (Wang et al., 2023) manipulates the entire dataset through processes such as inversion and rotation to create a pseudo-class dataset. Subsequently, a classification model is employed to predict the classes of the manipulated pseudo-class data. They posit that, given the rarity of anomaly data, the generalization performance during training is poor, leading to lower pseudo-label scores. These label scores are then utilized as weights on the loss values, effectively reducing the loss and further differentiating the data, thereby identifying anomalies. Employing a self-supervised discriminative network as a truth discovery mechanism to detect anomalies in data presents a viable approach. However, several issues arise, such as the network's diminished performance when the proportion of anomalies is significant. In situations where there is a high volume of anomalies mixed in with normal data, traditional methods often struggle to accurately differentiate, resulting in suboptimal detection outcomes.

To address these problems, we propose a self-supervised discriminative (SSD) model with trust awareness as a truth discovery mechanism. We incorporate the credibility of workers into the SSD model. Workers with high credibility have a greater influence on the SSD, while those with low credibility have less impact on the model. We then update the credibility of workers based on the output scores of the model. The main contributions can be summarized as follows:

(1) We propose a trust-aware SSD-based data quality assessment method to improve the accuracy and efficiency of image data authenticity evaluation, addressing the limitations of traditional truth discovery methods that cannot be applied to image data.

(2) We incorporate the credibility of workers into the SSD, enabling the traditional self-supervised anomaly detection model to resist collusion attacks to a certain extent.

(3) Simulation results show that our proposed model significantly outperforms traditional anomaly detection approaches, especially for high proportions of anomalous data.

2. Related Work

Currently, the researchers often assume that all workers are benign, and data quality assessment and filtering are focused on the angle of shooting or image clarity (Guo et al., 2017). Unfortunately, malicious workers can provide carefully crafted outliers to evade filtering (Fang et al., 2021). Many works have made great efforts to effectively discover ground truth from noisy or even conflicting perceptual data. Garcia-Ulloa et al. (2017) proposed a novel method based on recursive Bayesian estimation from multiple user reports to address the difficulties in truth discovery in spatiotemporal tasks. Li et al. (2014b) proposed a confidence-aware truth discovery method that can automatically detect truth from conflict data with long-tailed phenomena. This method not only estimates the reliability of the information source, but also considers the estimated confidence interval, making it effective at reflecting the true reliability of different levels of participation of the information sources. Wang et al. (2017) proposed a novel distributed truth discovery framework, which can effectively and efficiently aggregate conflict data stored on distributed servers, considering the differences between objects and the importance level of each server. Yang et al. (2019) used truth discovery methods to implement unsupervised detection of fake news. However, such schemes are typically tailored to structured data (i.e., decimal measurements or binary observations), and thus cannot handle unstructured photos.

In the field of image processing, several anomaly detection (AD) methods have been proposed to identify exceptional values in training sets uploaded by workers. Early approaches included clustering-based methods that treated data not belonging to any primary data cluster as outliers (Jiang et al., 2001; Liu et al., 2008). However, the image data's unique spatial structures and rich semantics make traditional anomaly detection methods ineffective. With the development of neural networks, Chen et al. proposed using AutoEncoder for outlier detection. Nevertheless, this approach requires pretraining with normal data sets, and the presence of outliers in the training set can significantly affect the model. E^{3}Outlier (Wang et al., 2023) uses self-supervised learning, which is currently a popular research topic to detect anomalies, cleverly leveraging both the internal priority and uncertainty of networks. However, these methods rely on the assumption that outliers are less common than normal data. If workers launch conspiracy attacks (Gong and Shroff, 2018), excess abnormal data will render the AD schemes ineffective and even mislead the model.

3. System Model and Problem Statement

We consider a typical VCS consisting of a group of M workers, where $M = 1, 2, ..., M$, each with a corresponding trustworthiness degree T_m. The primary goal of the platform is to publish a sensing task and collect data from the workers. The workers are distributed throughout the city and carry mobile devices with strong communication and storage capabilities. The workers act as image data collectors who accept published sensing tasks and submit the collected data upon task completion. However, the data uploaded by workers is often uneven. Honest workers contribute truthful information while malicious workers may upload fake data to deceive truth discovery models.

Then, the goal of the system is to identify low-quality task results from massive task results. This problem can be modeled as a binary classification problem. To address the problem, we plan to design a scoring model S. Given input x with worker's trustworthiness, the objective of S is to output $S(x)$ as close to 1 as possible, indicating a higher likelihood of normality, and as close to 0 as possible, indicating a higher likelihood of abnormality.

4. Model Design

4.1. The Trust-aware SSD Model

Since in the VCS, the task results submitted by workers are unlabeled, we implement the scoring system S based on the SSD to distinguish the quality of the task results submitted by workers. Inspired by E^3Outlier (Wang et al., 2023), we designed a truth discovery method with a trust-aware SSD. Figure 2 provides an intuitive representation of the SSD.

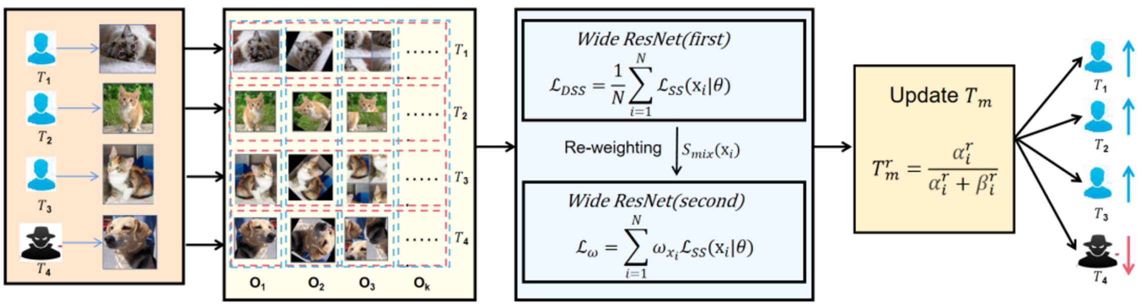

Figure 2: The framework of the system S.

Firstly, the image data submitted by the workers will be used to generate a new dataset along with corresponding pseudo-classes (pseudo-labels) through geometric transformation operations. These operations are described in detail in E^3Outlier. Assuming a total of K operations are designed to create pseudo-classes, and the generated image data is denoted as $X' = \left\{\mathrm{X}^{(1)}, \mathrm{X}^{(2)}, \cdots, \mathrm{X}^{(\mathrm{K})}\right\}$ with labels Y. Then, we build an SSD model with the Wide ResNet (WRN). In the first WRN, its optimization goal is to minimize the following objective

$$\mathcal{L}_{\mathrm{DSS}} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathcal{L}_{\mathrm{SS}}(\mathrm{x_i}|\theta) \tag{1}$$

where $\mathcal{L}_{SS}(\mathrm{x}_i|\theta)$ denotes the loss value generated during the self-supervised learning process.

A key to effective differentiation between normal and anomalous labels by the SSD is the design of data manipulations. These manipulations must enable Deep Neural Networks (DNNs) to not only perform classification tasks on pseudo-classes but also to capture the high-level structural semantics within images. For instance, to determine the type of rotation applied to an original image, a DNN must learn to locate prominent objects within the image and recognize the orientation of their higher-order components, such as the head and legs of a human figure. In this paper, we employ operations such as Regular Affine Operations (RAO), Irregular Affine Operations (IAO), and Patch Re-arranging (PR) to create pseudo-classes. These operations compel the deep neural network to grasp the high-level structural semantics of images. Given that normal labels often dominate in annotated data, the model is better able to understand the high-level structural semantics of normal label images. This leads to more accurate classification predictions for pseudo-classes and higher probability values output by the Softmax layer.

Based on the aforementioned conclusions, it's intuitive to consider using the average value of the probabilities output by the Softmax layer as a measure of whether a label is anomalous or not.

Specifically, for an image $\mathrm{x}^{(y)}$, let $S_{avg}(x)$ be the average of $P^{(y)}(\mathrm{x}^{(y)}|\theta)$ across K correct pseudo-classes, which can be mathematically represented as follows:

$$S_{avg}\left(x\right)=\frac{1}{K}\sum_{y=1}^{K}P^{(y)}(\mathrm{x}^{(y)}|\theta) \tag{2}$$

Although this method has achieved certain results, there is still room for improvement. To enhance performance, a more comprehensive approach could be adopted to evaluate the model's predictive certainty. For instance, considering the entropy of the entire probability distribution, the E^3Outlier framework utilizes negative entropy as a method to measure the model's predictive certainty. Negative entropy, a measure of the amount of information or the uncertainty of a system, is employed in this context to assess the certainty or confidence of model predictions, taking into account the entire probability distribution output by the model. This enables negative entropy to more comprehensively capture the uncertainty of model predictions, especially when there are multiple similar and highly probable categories in the model's output. The formula is as follows:

$$S_{ne}\left(\mathrm{x}\right)=\frac{1}{K}\sum\nolimits_{y=1}^{K}\sum\nolimits_{t=1}^{K}P^{(t)}\left(\mathrm{x}^{(y)}\mid\theta\right)log\left(P^{(t)}\left(\mathrm{x}^{(y)}\mid\theta\right)\right) \tag{3}$$

Then, another distinction from the E^3Outlier approach is that, to tackle scenarios potentially involving collusive attacks or a significant volume of anomalous data, we employ the reliability of workers as weights to amplify the differentiation between anomalous and normal data. Thus, the reliability T_m of the worker m is multiplied by the loss value $\mathcal{L}_{SS}\left(\mathrm{x}_i\mid\theta\right)$. More specifically, we multiply the worker's credibility T_m with $S_{mix}(x)$ to act as the weight $\omega_X=\{\omega_{\mathrm{x}_1},\omega_{\mathrm{x}_2},\cdots,\omega_{\mathrm{x}_N}\}$, ensuring that $\sum_{i=1}^{N}\omega_{\mathrm{x}_i}=1$. Therefore, the calculation formula is:

$$\omega_{\mathrm{x_i}}=\frac{\mathrm{T_{x_i}S_{mix}\left(x_i\right)}}{\sum_{\mathrm{j=1}}^{\mathrm{N}}\mathrm{T_{x_j}S_{mix}\left(x_j\right)}} \tag{4}$$

T_{x_i} represents the credibility of the uploaded worker corresponding to image x_i. The goal of the second WRN is to minimize the loss value as follows:

$$\mathcal{L}_{\omega}=\sum\nolimits_{i=1}^{N}\omega_{\mathrm{x}_i}\mathcal{L}_{SS}\left(x_i\mid\theta\right) \tag{5}$$

4.2. Trust Update

To evaluate a worker's trustworthiness, we model the probability of a worker performing a task honestly as a Bate distribution, i.e., $Beta\left(\alpha_m^r,\beta_m^r\right)$. α_m^r and β_m^r represent the success factor and failure factor of worker m in $r-th$ trust updated, respectively. As a result, The trustworthiness of worker m can be modeled as the mean of this distribution, i.e.,

$$T_m=\frac{\alpha_m^r}{\alpha_m^r+\beta_m^r} \tag{6}$$

Let $S_\omega\left(\mathrm{x}_i\right)$ represent the output the model S when input data x_i. Then, if $S_\omega(x_i)$, then the value of α_m^r will increase by

$$\begin{cases}\alpha_m^r=\alpha_m^{r-1}+\mu S_\omega\left(\mathrm{x}_i\right) \\ \beta_m^r=\beta_m^{r-1}\end{cases} \qquad S_\omega\left(\mathrm{x}_i\right)>=\varepsilon \tag{7}$$

This means that the trustworthiness of workers will improve when the submitted data exceeds the quality threshold ε. Otherwise, when the value of $S_\omega\left(\mathrm{x}_i\right) < \varepsilon$, our strategy is to increase the value of β_m^r by a negative factor τ, i.e., Equation 8. The trustworthiness of workers will decrease when the submitted data falls below the quality threshold of ε.

$$\left\{\begin{array}{c} \alpha_m^r = \alpha_m^{r-1} \\ \beta_m^r = \beta_m^{r-1} + \tau\left(1 - \ S_\omega\left(\mathrm{x}_i\right)\right) \end{array}\right. \qquad S_\omega\left(\mathrm{x}_i\right) < \varepsilon \tag{8}$$

Usually, ε represents the threshold score determined by the platform to eliminate the last percentile of workers based on their rankings. Initially, we set $\alpha_m^0 = 1$ and$\beta_m^0 = 1$. By incorporating trust perception into the SSD, it can further differentiate between normal and anomalous data and resist collusion attacks to a certain extent.

5. Experiments

5.1. Benchmark Datasets and Evaluation

Due to the scarcity of datasets in Crowd Sensing, we synthesized a dataset using 50 workers whose responses follow a normal distribution, as well as standard datasets such as MNIST, CIFAR10, and SVHN. The workers were randomly allocated normal and anomalous data from the dataset in proportion, where all the normal data came from classes with common semantic concepts (e.g., "1" in MNIST), and anomalous data were randomly sampled with an anomaly ratio ρ from other classes in the same dataset. We set ρ at values of 0.1, 0.2, 0.3, 0.4, and 0.5. Due to the potential coordination between attackers, anomalous data were randomly sampled from only one class in this case. The experiment involved selecting and dividing a specific anomalous class from the dataset into multiple parts. Each colluding worker was assigned one part of the anomalous class data, aiming to collectively introduce a biased distribution of the target anomalous class by proportionally uploading their respective parts. In the baseline test, each class was sequentially treated as normal data, and the performance of all classes was averaged to obtain the overall anomaly detection performance on the baseline test dataset. Since all images were considered unmarked in the model, we did not perform a train/test split and merged them for experimentation. All experiments were repeated five times with different random seeds to obtain average results. We employed the commonly used area under the receiver operating characteristic curve (AUROC) as threshold-independent metrics.

5.2. Compared Methods

We compared our proposed approach to multiple existing AD methods, including state-of-the-art solutions: (1) **E^{3}Outlier** (Wang et al., 2023) proposes to use currently popular self-supervised learning, cleverly exploiting the characteristics of internal priority and network uncertainty to detect anomalies, which has excellent performance. (2) **Convolutional Autoencoder (CAE)** (Masci et al., 2011). A method widely used in many unsupervised learning tasks for processing image data. (3) **CAE+IF** (Cruz et al., 2019). A popular classical anomaly detection method based on CAE and isolation forest. (4) **Discriminative Reconstruction-based Autoencoder (DRAE)** (Xia et al., 2015) distinguishes outliers by threshold processing the reconstruction loss of CAE using an adaptive solution and integrates it into the loss function to improve anomaly removal performance. (5) **Deep Autoencoder Gaussian Mixture Model (DAGMM)** (Zong et al., 2018) embeds GMM parameter estimation network into CAE and achieves outlier detection by simultaneously performing representation learning and fitting GMM. (6) **SSD+IF.** It shares the SSD part of E^3Outlier but inputs the representation learned by an SSD to the IF model for anomaly detection. For the evaluation of worker weights, we initially adopted the S-Means approach, where we consider the weighted average of model scores for data submitted by each worker, with MAE serving as the baseline. To facilitate a comparison with the mainstream weight updating method, CRH, we incorporate its principles into our model by replacing the worker's task completion accuracy with the model's output and subsequently normalizing it.

5.3. Experimental Results

The AUROC comparison at different anomaly percentages is shown in Figure 4. As shown in Figure 3, it can be observed that TASSD has a significant advantage compared to other methods. Compared to the state-of-the-art algorithm E^3Outlier, TASSD achieves a 3%-8% higher AUROC, achieving a leap in performance.

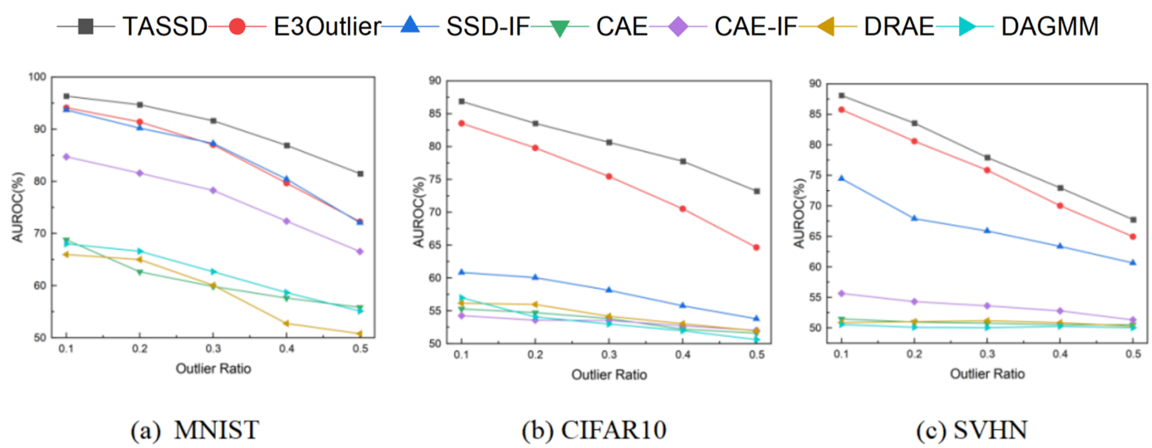

Figure 3: We compare the AUROC of various methods with our proposed TASSD algorithm under different proportions of anomalous data.

In the simple dataset MNIST, TASSD exhibits a gradual increase in AUROC as the outlier ratio increases, outperforming other advanced algorithms such as E^3Outlier and SSD-IF, indicating its ability to withstand malicious data attacks from workers and maintain outstanding performance even under collusive attacks. In the color dataset (CIFAR10/SVHN), except for our TASSD and the advanced algorithm E^3Outlier, the performance of other algorithms is quite poor, especially in the case of high anomaly rates in CIFAR10, TASSD still exhibits excellent robustness.

To validate the superiority of the Beta algorithm employed in our worker weight optimization algorithm, we conducted experiments using the MNIST dataset as a case study. Each class was trained sequentially. Figure 4 illustrates the performance of different weight algorithms under $\rho = 0.1$ and $\rho = 0.3$. It can be observed that the Beta distribution exhibits superior convergence and stability in terms of MAE.

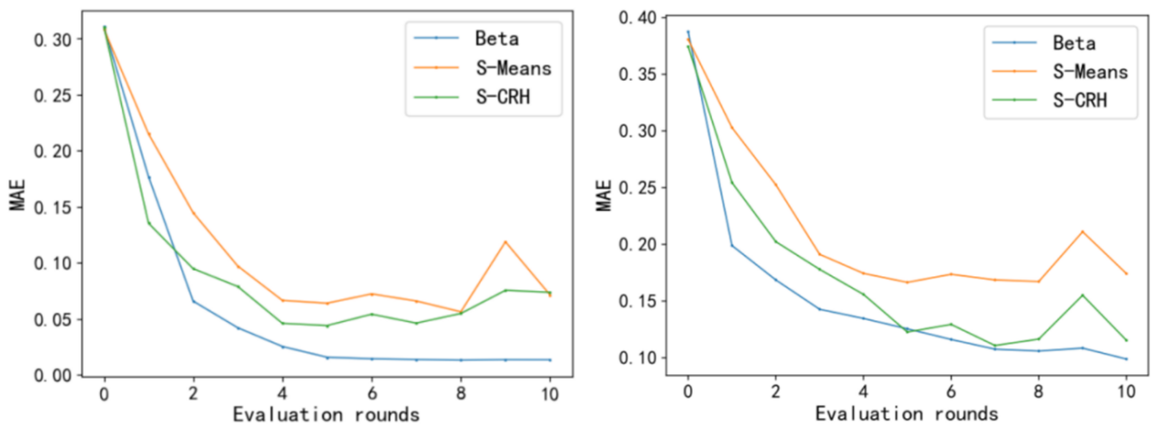

Figure 4: Performance Comparison of Algorithms at $\rho = 0.1$ and $\rho = 0.3$.

6. Conclusion

In response to the difficulties of applying traditional truth discovery methods to image data, this paper proposes a method based on SSDs with trust perception for data quality evaluation, thereby improving the evaluation accuracy and efficiency of image data authenticity. This method innovatively introduces worker credibility into the SSD, enabling the model to better handle collusion attacks and other issues. A re-weighting mechanism is also designed for the model to deal with disguised attacks from malicious workers who may have acquired high trustworthiness. In terms of experimental simulations, the proposed method is compared with traditional anomaly detection schemes, and the results show that the proposed method has significant advantages at higher anomaly data ratios. In summary, this research provides a more robust and reliable method for assessing data authenticity in Crowd Sensing systems, which is of great significance for improving the practical application value of Crowd Sensing. In future research, the effectiveness of the model can be further explored in different scenarios, and improvements and optimizations can be made to address its potential limitations.

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