IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
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Innovative Method for Predicting Vehicle Speed Detection Using Fuzzy Local Information Means and CNN

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***Abstract* – Thanks to technological advancements, we now have a number of options for obtaining traffic data. Yet, the precision with which various technologies measure drivers' actual speeds varies greatly. It is a widespread complaint among transportation researchers and professionals that they lack information of device accuracy. This study employs video data image processing alongside the Euclidean distance approach to estimate vehicle speeds from a variety of perspectives. To begin, the proposed approach applies preprocessing to the frames we retrieved from the video data in order to reduce the shadow impact. Then, we use a Gaussian Mixture Model (GMM) to pull out the foreground from the background. The next step is to apply a median filter on the resulting foreground. Using Haar Wavelet decomposition for feature extraction, appearance-based hypothesis verification ensures the correctness of hypotheses based on their outward appearance. After that, FILM-CNN is used to train the model which outperforms k-Means and CNN methods.**

***Keywords*— Gaussian Mixture Model (GMM), Haar Wavelet Transform (HWT), Fuzzy Local Information Means (FILM).**

I. INTRODUCTION

As the urban population grows, so do the challenges people face in their daily lives, such as increased traffic congestion caused by a mismatch between rising demand and inadequate road capacity and infrastructure. As these issues have substantial day-to-day repercussions, it's crucial to find effective ways to mitigate them. The detection of vehicle speeds is crucial for the enforcement of speed limits and for providing evidence of current traffic conditions. Historically, radar equipment like the radar gun and radar detector was used to detect or monitor vehicle speeds. The major objective of speed monitoring systems is to provide law enforcement with greater resources for efficient traffic control. Radio Detection and Ranging (RADAR) and Light Detection and Ranging (LIDAR) systems are commonly used to ascertain a vehicle's speed. A RADAR gadget broadcasts a radio wave, which is then reflected by the car and picked up by an antenna. The traffic radar receiver determines the moving vehicle's speed by comparing the carrier frequencies of the original and reflected signals. A LIDAR gun measures the time it takes for a light pulse to travel from the gun to a vehicle and back. With this information, LIDAR can instantaneously calculate how far away the gun is from the car. By taking many measurements at regular intervals and comparing the distance the vehicle traveled between each set of measurements, LIDAR can accurately determine the speed of a moving object. Industries of all stripes have adopted the use of radar technology to measure velocity. Yet, there are limitations to the equipment that cannot be overcome so long as it is based on the radar technique, regardless of how far technology has progressed. Doppler shift phenomena describes how radar works. It is probably encounter on a daily basis. Doppler effect happens when sound is produced or reflected by a moving object. Scientists can determine the speed of a moving vehicle by measuring the frequency shift caused by the Doppler effect as sound waves from the boom echo back to the wave generator. The velocity of a sizable fleet of cars can be calculated using any number of established methods. It is suggested that the bulk of a system for measuring velocity lies in the identification and tracking of objects. In the method of frame differencing is outlined, which can be used to spot moving objects. If there is no motion in the background, this method is highly effective. Gaussian mixture modeling is introduced as a solution to the problem of foreground subtraction from a dynamic background. Because it can determine both the direction and velocity of an object's motion, optical flow is useful for tracking purposes. Using a Raspberry Pi as the embedded device to detect vehicle speeds is featured in a fascinating project detailed in[1]. The Gaussian Mixture model's performance in resolving the issue of object detection indicates the method's transferability even to settings with limited resources. An illustration of using corner detection to infer speeds from video frames [2]. Because to developments in computer vision algorithms, recent studies have proposed utilizing vision as the only mechanism for calculating vehicle speed.

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Because video cameras flatten the world into a 2D plane, speed calculations and distance could be imprecise. Because of this intrinsic limitation, the digital representation produced has accuracy proportional to the inverse square of the distance between the camera and the vehicle. Notwithstanding of these limitations, video cameras present a promising alternative to more expensive range sensors like microwave Doppler radars and laser-based devices. The usage of preexisting traffic cameras is another perk that does not necessitate the acquisition of new sensors.

II. LITERATURE SURVEY

It is vital to maintain track of individual cars in order to build a credible model for calculating vehicle speeds. Several approaches based on conventional computer vision and machine learning methods have been developed for object tracking. [3]merged a conventional optical-flow approach with motion vector estimations to solve the object tracking problems. A track-by-detect strategy was proposed, with optical-flow methodology for detection and motion vector estimate for velocity estimation. [4]used a Kalman Filter into a reinforcement learning system to handle a non-stationary setting. We propose recasting the video object tracking problem as one of predicting the location of a target object's bounding box in the subsequent frame. [5]proposed a method to automatically detect drunk driving and speeding on South African roadways, eliminating the need for a manual approach. This innovation in transportation made use of cloud computing, VANETs (vehicular ad hoc networks), and the Internet of Things (IoT). In recent years, researchers have paid a lot of attention to the concept of VANETs. It uses technology that can back up an ITS[6]. Adopted for its ability to update drivers on traffic conditions in real time, it has helped raise standards in transportation and boost security and transparency. It can also be used to enhance the in-car entertainment system for the comfort and enjoyment of passengers[7]. In order to improve road safety and enable remote traffic control, VANETs now employ the IEEE 802.11p [5] standard for dedicated short-range communication (DSRC). Current control systems rely too heavily on human input to be effective in all but the most ideal situations. Maintaining orderly traffic flows requires a system that is regularly updated via satellite. This might be possible with the help of internet protocols and the IoT. Several methods for determining vehicle speed based on video sequences are shown in [8]while an innovative technique for doing so based on a single, fuzzy image is described in [9]. You can learn more about the topic of motion in digital images by consulting [10]. There have been numerous articles written about the difficulty of keeping up with moving objects and people in traffic. Several books and articles discuss various LPR methods that can be used to automobiles. The method for edge identification in grayscale images reported in combines adaptive thresholding and template matching. The method reported in [11]utilized a fuzzy-logic strategy to find the license plate, while topological properties and a neural network identified the written characters. Optical flow vectors have been used with lateral views after camera calibration in [12]and with traffic photographs. [13]propose using stable characteristics for vehicle tracking, and suggests using a single blurred image for license plate detection and tracking to estimate the cars' relative motions. There is no universal standard for validating the various methods. The outcomes of traffic speeds rather than vehicle speeds were presented in certain works[14]. Although speed was cited as a factor in several situations [15]this is not always the case. As mentioned in [16]using the speedometer as a proxy for the true speed is not wholly reliable because most automobile manufacturers intentionally skew the device. Aerial imagery served as the basis for one of the approaches taken to generalize vehicle speeds[17]. A path between two frames can be calculated using the optical flow method and the K-MEAN clustering algorithm. Moving object values and frame time are used to estimate the average vehicle speed in image scale, which is then converted to real scale. This method is 12% off the mark. An alternate method, based on the optical flow algorithm for determining the vector of item movement, was developed for use with footage from a camera installed above the road[18]. Here, image-analysis software is used to process each of the frames and the displacement vectors it contains. Objects' velocities are calculated when the data is processed further. Above-road cameras can be adjusted for more accurate measurements [19]. Before beginning the video processing method, it is required to measure the height and tilt angle at which the camera is suspended. Using computer vision techniques, the system can identify moving objects and calculate their speed. Methods that detect edges near the boundaries of each blob, as described by[20], and methods that extract features like Laplacian, color from blobs and derivatives, face the same problems. In Section VII,it's discuss how our system stacks up against a particle filter-based blob tracking method, similar in principle to that proposed by[21]'s approach circumvents blob analysis' limitations by directly following landmark features. Their approach, however, is limited to one vehicle at a time because it presumes that all the recorded attributes are associated with the same vehicle. They also ignore depth perception and necessitate a side view of the cars. [22]suggested a pipeline for a video-based speed estimation system. License plate locations on moving vehicles were approximated using a license plate detector in this arrangement. To calculate the velocity, it's first used to track the features retrieved from the plate region in each frame using a homograph matrix. The homograph matrix was generated by matching four image points to their equivalents on the ground plane. [23]suggested a license plate-based video-based speed estimation method. In contrast to the work in [22]this proposed approach to accounted for the license plate's elevation above ground level. Calibration of a camera can be difficult, but the external factors that affect it should be understood. The exact height and orientation of the camera must be established. Stable tracking of the vehicle even in challenging settings, accurate camera calibration, real-time operation, and low cost are thus necessary for a successful vision-based vehicle speed estimation system. Results provided using a method based on blobs, edges, or picture patches can be thrown off by shadow, perspective, and lighting variation. This proposed used to developed a point

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tracking system in our previous work [24]to deal with traffic and bad weather. [20]eliminated image noise and then isolated blob features like Laplacian and color. There is currently no solution to the open challenge of stable vehicle tracking in high-traffic conditions in computer vision. So, the car's characteristics rotate on a phantom plane that's perpendicular to the ground. One common method of dealing with this problem is deriving a correction factor based on the height of the vehicle's features above the road. The proposed approach uses FLIM – CNN to train the model.

III. PROPOSED SYSTEM

In this paper, we will go over each of the five steps that make up the system architecture used to get an estimate of a vehicle's speed from the available data. Each step will do a discrete task, and the output will be used in the subsequent steps until the final estimated speed is determined. Fig. 1 is a block diagram of this system.

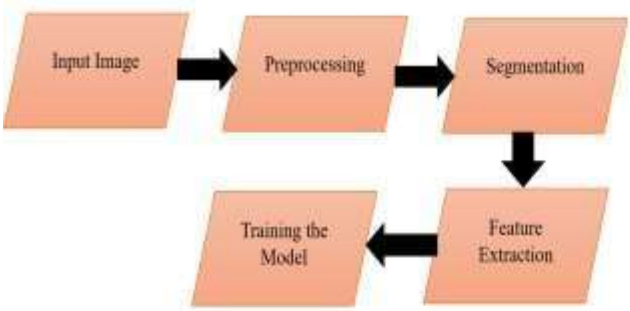

Fig. 1. Proposed Model Flow Diagram

A. *Preprocessing*

Preprocessing is conducted to each frame of video data before it is subjected to background subtraction. Bold shadows that could be mistaken for solid objects can be reduced through preprocessing [25]. In this work, we employ a general equation for adjusting brightness and contrast as a preprocessing step:

$$(k, i) = \gamma h(k, i) + \alpha \qquad (1)$$

where $h(k,\ i)$ is the intensity of a pixel located at coordinates (k, i), α is the gain parameter set to 1, and is the bias parameter set to 0. Histogram of image result from background subtraction procedure shows that decreasing α and increasing β with a given change of and minimizes bold shadow, which can be detected as solid object.

B. *Smoothing:*

Background subtraction might result in a lot of unwanted noise, but smoothing can help filter it out. Background subtraction tends to produce salt-and-pepper noise, which can be mitigated with the help of a median filter.

C. *Segmentation:*

The Gaussian mixture model, an adaptive background subtraction technique, forms the basis of our strategy. When the background is subtracted from each pixel, the foreground is divided into clusters using the DBSCAN clustering method, and each cluster is then assigned a Bounding box to denote its location.

1) *GMM:*

GMM is a typical technique for segmenting moving regions in images in real time. The most appropriate Gaussian distribution is used to determine whether a pixel belongs in the foreground or background.

The equation describes the pixel history (z_0, x_0) at time s.

$$Z_1, \cdots, Z_s = \{W(z_0, x_0, k) : 1 \le k \le s\} \qquad (2)$$

A combination of L Gaussian distributions (L) is compute performance-based [26]; higher numbers require better hardware) is used to simulate each pixel's past. The odds of seeing the current pixel value are

$$(Z_S) = \sum_{k=1}^{L} \alpha_k, s^y\ (Z_s \sigma_{k,}, \sum_{k,s}) \qquad (3)$$

where $\sum$ is the covariance matrix, and where η is a Gaussian probability density function, $\alpha_k,\ s$ is an estimate of the weight of the k^{th} Gaussian in the mixture at time s, and $\sigma_{k,s}$ is the mean value.

$$\eta(Z_s\ \sigma_{k,s}, \sum_{(i,t)}) = \frac{1}{(\frac{2}{\pi})^{\frac{m}{2}} \sum_{k,\,0.5}} exp - \frac{1}{2}(Z_s - \sigma_{k,}) \sum_{k,s} (Z_s - \sigma_{k,s}) \qquad (4)$$

$$\sum_{l,s} = \emptyset_s^2 K \qquad (5)$$

To get Equation (5), we assume that the pixel values for red, green, and blue are uncorrelated and have the same standard deviations. GMM relies on Vehicle speed detection to maximize the likelihood of observed data, however since VSD would be expensive to implement for every pixel, On-line K-means approximation is used instead. Until there is sufficient and consistent evidence for a Gaussian that contains them, pixel values that do not fit the background distributions are classified as foreground.

D. *Feature Extraction:*

1) *Haar Wavelet Trasnform*

Wavelets are a multiresolution function approximation that can be used to break down a picture or signal into smaller, more manageable pieces. They have been effectively implemented in solutions for a wide range of issues, such as object identification, facial recognition, and image retrieval[26]. Every wavelet decomposition of a signal uses only two waveforms (mother wavelets). Wavelets (wavelet basis) at various places and sizes are generated by translating and scaling the two shapes (durations).

E. *Training the Model*

1) *CNN*

Both methods use CNNs to identify environmental features. In order to recognize objects, R-CNN is used. This algorithm makes value-free comparisons is RPN-based convolutional network. The areas of the network are established by dragging the object suggestions window across convolutional feature maps. This spatial window is used to gather low-dimensional characteristics for

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subsequent layers to utilize. The use of regression and classification. The anchors were positioned deliberately to bring back the most promising regional suggestions. The size of the window for each anchor will be modified so that thorough data queries can be performed. Take into account: The windows on anchors number five. The total number of windows employed is proportional to the size of the feature map. The primary output is a list of what can be seen. This list has multiple applications to create an object list to pinpoint the focal points of the scene.

Five layers, including an input, an output, and three hidden unit layers, are used in S-CNN. As a first step, several hidden layers activate the filtering and pooling capabilities of convolution layers. After input, features that are not affected by changes in scale or translation are extracted using convolutional filtering and pooling. The final hidden and output layers finish the classification process. The analysis of KPD (key point discriminators) made use of the filtering and pooling capabilities of convolution layers. The S-input CNN's layer receives a 2D array of data representing the scene's many objects, as well as KPD derived from feature extraction, the scene's background object concentration, color density, and regional information. This ensures that the data is correct. The visual data inputs are filtered in this section. Information is filtered by these mechanisms. The third hidden layer is activated based on the linearly concatenated characteristics of the second. Linear addition was used to combine the projections from the second hidden layer. Neuronal circuit activation aided in the creation of predictive classes. You can accomplish this by employing S-CNN to categorize environmental features. After considering data from R-CNN and FLIM, a classification for vehicle speed Identification will be reached. Training relies on a large number of labeled, identical samples. These non-biased links are put through their paces in a performance and analysis test.

1) Fuzzy Local Information Means Algorithm(FLIM):

In the past, vector quantization was used by traditional K-Means clustering. Most of the time, the center of the cluster is determined by random using a recursive process that then adjusts the way distances are calculated. The average from the preceding cycle is used to locate the cluster's center [27]. This computation is done at each iteration. Clusters will be recalculated indefinitely until convergence is achieved. At complete convergence, the K-centers move. What's going on is what's triggering this. There are three components to the classic K-Means algorithm: the convergence function, the recalculation of the cluster centers, and the cluster bin.

$$D_h = \sum_{k=1}^{md} (D_d k - MD_d k^2) \qquad (6)$$

$$MD_d k = \left(\frac{1}{mad_k}\right) \sum_{i=1}^{mad_k} Dbin_k \qquad (7)$$

$$Dbin_k = Dbin_k \,|Z_u\, k \qquad (8)$$

$$Z_u k = lim_{i=1\ to\ mz}\ z_i\ if\ dist\ of\ \ \text{min}\ to\ D_d\ k \qquad (9)$$

$$dist = y_i - D_d\, k^2 \left\{\frac{= 1\ to\ mz}{k = 1\ to\ md}\right\} \qquad (10)$$

The function determines the distance between cluster centers. Accuracy is required to set halting criteria and regulate repetitive stages. This reflects the clusters that the user has selected or are available. Current and planned cluster nodes are compared in this section. The number of cluster bins is calculated using the formula where and are equal, where is the cluster bin we defined earlier. There should be as many clusters as there are bins. If two points or elements are at least the minimum distance away, then that's the number of accessible data elements.

The following are some of the drawbacks of this approach to assessing data processing quality: In a linear fashion, (6). So, data stored in one cluster is inaccessible to users in another cluster, however this is not necessarily in real-time. Convergence to the local minimum, rather than the global minimum, is possible with the K-means approach. Even though the global minimum has a role, the initial random selection still has an effect on the final cluster. Keeping the cluster centers from shifting too much between iterations raises the total time complexity. As a result, we get the fuzzy local information means (FLIM), which we'll go through now.

$$lin_{ik} = \frac{1}{aki}(Max(y) - D_d k)^h \qquad (11)$$

The data displayed by Equation (11) is localized to each cluster. This is calculated by measuring the arithmetic inverse of the distance between the centers of the two clusters. By calculating the minimum convergence rate and then pushing cluster centers in that direction, this function finds the optimal solution. If this is the case, then the membership function of FLIM is identical to that of K-mean (equation (12)), which means that FLIM also enhances the push-in cluster center selection parameter.

$$MD_d k = \left(\frac{1}{mad_k}\right) \sum_{i=1}^{mad_k} P^h k + lin_{ik} \qquad (12)$$

$$P^k l = Z_u l \forall Y_l \qquad (13)$$

The user-requested cluster size, denoted by M and md, is used here. Each constituent in a cluster group is given a weight, or " ," to indicate its relative importance. In addition to being the function that is used to calculate $D_d k$, $MD_d k$ is also the function that stores the clusters that have been formed as a result of $D_d k$ (13). The clusters $Z_u k$ that have been formed as a result of the previous computation are also considered by the function. The unique features that set FLIM distinct from other methods. The standard K-means calculation method would not have involved the presence of this fuzzy characteristic, denoted by the notation $P^k l$. Some individuals inside a cluster group may be located in a different cluster.

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$$Z_u l = lim_{i=1\ to\ my}\, y_i\ if\ a_{ki} of\ z_i is\ \min to\ D_d\ l \qquad (14)$$

$$a_{ki} = y_k - {}^{2}_{d}\frac{\{^{=1\ to\ mz}\}}{k=1\ to\ md} \qquad (15)$$

Equations (14) and (15) show the data that was chosen for each cluster and the distance measurement that was conducted between the data items and the group. How well the data points matched the cluster was assessed by this. After this selection is made, cluster importance is increased for data points that include individuals and decreased for quasi data sets.

$$obj\ h = \sum_{k=1}^{md}\sum_{i}^{mz} N^h ze_{ki} + lin_{ik} \qquad (16)$$

The degree of convergence is also determined by the recursive process, which identifies the objective function making the decision. Convergence in optimization issues is determined in part by membership variables that function in conjunction with data-specific knowledge parameters. This resulted in a successful workplace application of fuzzy k-means.

IV. RESULT AND DISCUSSION

Reference models including CNN and the K-Means algorithm were provided to validate the accuracy of the FILM-CNN prediction model suggested in this paper. Each model's predictions are output for comparison after being tuned using the same data set. In Figure 2, we see a comparison of the mean squared error (MSE) of several models. The graphic demonstrates that the prediction accuracy drops dramatically with CNN, FLIM-CNN models, and that the fitting effects of projected values and measured values vary between models. The FILM-CNN model outperforms the competition in terms of accuracy, with an MSE of just 0.0629. Next, K-Means was used, and its MSE was 0.3272. When compared to the FLIM-CNN model and the FLIM-CNN model, the MSE of a CNN was 0.4357, or around 4.9 times better.

Fig. 2. MAE Comparision of the

Error analysis and comparisons between predicted and observed values of the slope safety factor F helped researchers better grasp the predictive power of the FLIM-CNN, CNN, and K-Means models. Figure 3 depicts the spread of possible error values.

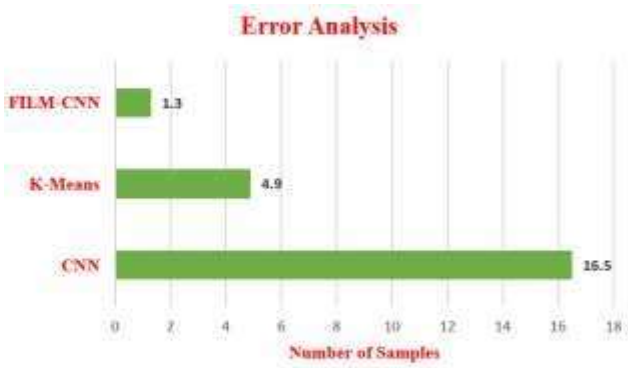

Fig. 3. Error Analysis of FLIM-CNN Model

Figure 4 shows the results of a simultaneous comparison of the predicted values from the FLIM-CNN model, the CNN model, and the K-Means model with the actual values.

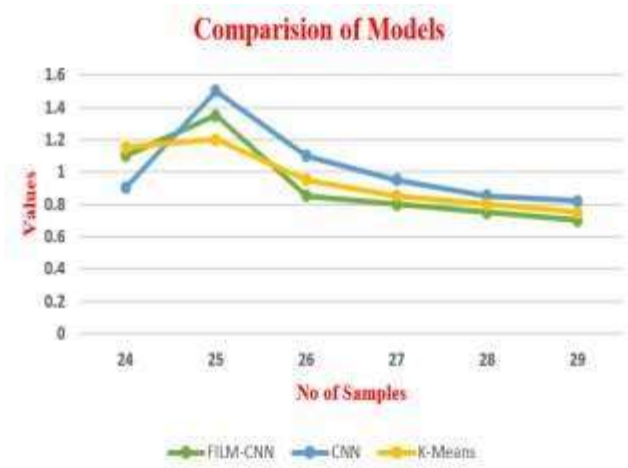

Fig. 4. RMSE of DAE-SVM Model

As can be seen in Figure 4, both the CNN and K-Means models' predicted values depart greatly from the true values. The CNN model's prognosis for samples 24 and 25 is particularly off, while the K-Means model's prediction for samples 25 and 26 is similarly off. The projected value and the actual value for each sample point are quite close to one another, showing that the FLIM-CNN model provides a greater fitting degree.

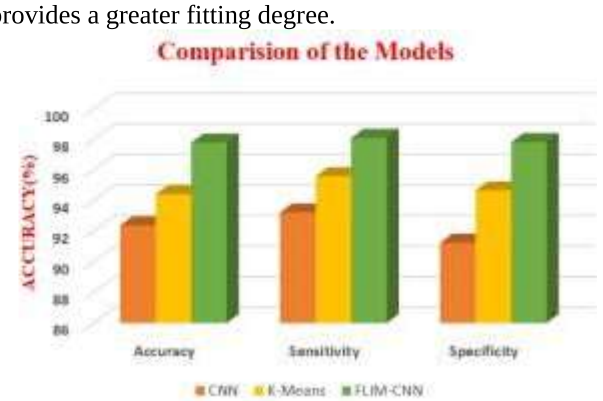

Fig. 5. Performance Evaluation of the Models

Figure 5 depicts a performance analysis of various methods. Figure 4 shows that when comparing the accuracy of CNN (92.39%), K-Means (94.43%), and the proposed FLIM-CNN based Vehicle speed detection approach (97.81%), the latter achieves the highest accuracy. Several studies support the speed prediction method based on FILM-CNN that was proposed.

V. CONCLUSION

Recent research efforts have focused heavily on the challenge of creating a robust and reliable vehicle identification and speed estimation system that can inform drivers of current road conditions and assist them in staying out of traffic congestion. The use of a camera and some form of image processing software to determine vehicle speeds is becoming increasingly common. Preprocessing, Smoothing, Segmentation, Feature Extraction, and Model Training are the five stages that make up the suggested method. Preprocessing in the suggested method include adjusting contrast and brightness. Once the background has been cleaned up with the GMM technique, the foreground image can be smoothed to get rid of any remaining noise. GMM is used to remove the backdrop. The suggested method relies on HWT to extract features. The suggested method employs FILM-CNN for model training. The proposed method achieves a higher accuracy (97.8%) than either the CNN or K-Means models.

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