Original Article

Comparative Analysis Of Various Machine Learning Models For Child Safety And Security System For Protecting Them From Child Trafficking And Assault

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Abstract

A novel algorithm is compared to a few different models that have been developed for the purpose of keeping children safe. The performance of the algorithm is evaluated by performing trials on a dataset and analysing the results of those trials. In this study, we conduct a comparison of the proposed method to three different types of neural networks: convolutional neural networks, recurrent neural networks, and long-term short-term memory. Neither of these types of comparisons has been done before. Photos that YOLOv4 deems to have questionable behaviour are marked as such, and the subsequent stage of the process, deep feature extraction, takes these pictures into consideration. The proposed model for the detection, alert, and classification of unknown behaviour produces classifiable findings through the use of the LCNN approach that was developed. The proposed HUADM-LCNN has a higher accuracy than CNN, RCNN, and LSTM, with a value of 0.87 being the benchmark for its performance. The findings of this study lead the researchers to the conclusion that the suggested activity identification and classification model, which includes the HUADM-LCNN implementation, provides performance that is superior to that provided by the standard classifier approaches. The proposed model for activity detection and categorization is therefore superior to the strategies that came before it in terms of its performance.

Keywords: CNN, RCNN, LSTM, YOLO, traditional classifier methods, LSTM, YOLO, and child safety

1.Introduction

The safety of children is a major concern in modern society; as a result, parents increasingly want to equip their kids with devices they don't understand and over which they retain complete control. The purpose of this discussion is to give safety measures for children when they are not in a predetermined area, by activating the gadget via an app on the parents' mobile phone. A camera-equipped wearable gadget is attached to the kid, allowing them to take pictures of their surroundings and upload them to an online storage facility. At the analysis stage, the cloud-stored photos are examined to determine which ones appear in more than three different shots[2]. After the camera captures a facial expression, an algorithm will evaluate it and notify guardians. When parents see something suspicious, they call the police. Images of people's facial expressions that will be used to infer their motivations are included in the dataset.

2. Materials and Method

2.1 Proposed System

As can be seen in Figure No. 1, the suggested system makes use of 365 view cameras that are all linked together via Arduino. These photos are taken by a camera. Sensors are utilised to determine the state of a child's health and prepare for an impending attack. If the readings from many sensors exceed a predetermined limit, the camera will switch on. The camera will begin taking pictures, which will subsequently be uploaded to the cloud. However, the proposed system can identify an adult's emotion in the same image as a children. The same information is supplied to parents to warn them of potential abuse.

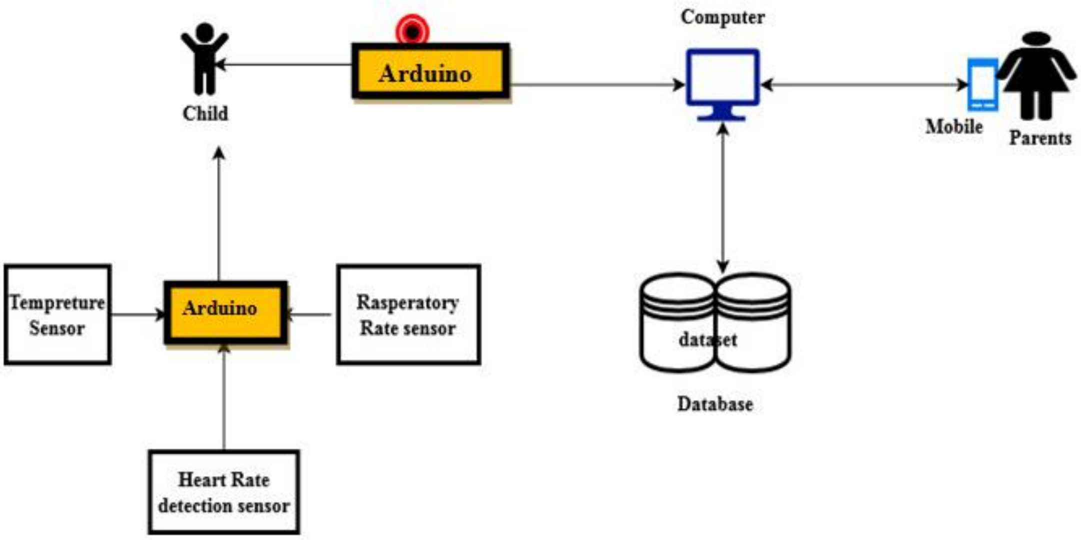

Figure 1: System Architecture

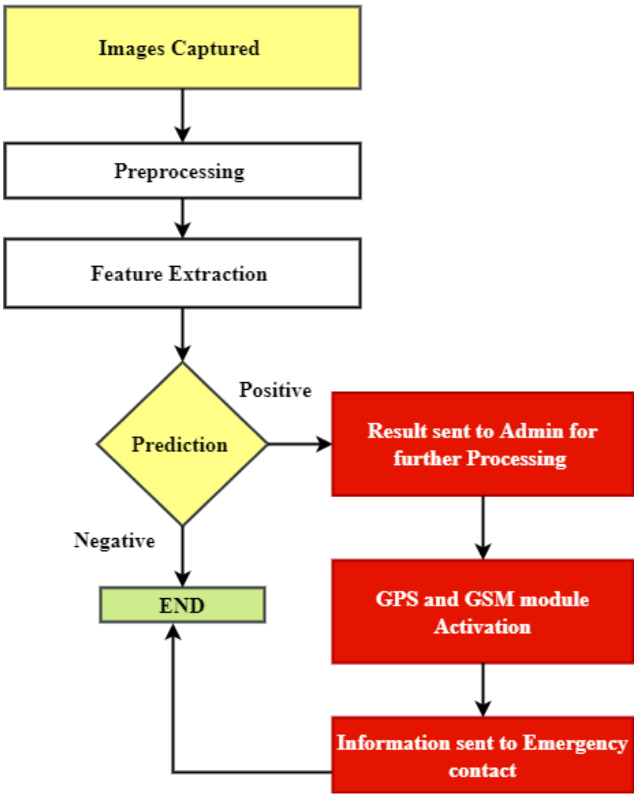

Figure 2 Flow Diagram of System

Figure 2 depicts the system's real flow. Input passed on for preliminary processing. Captured photographs have their features extracted, the suggested algorithm is used to make a threat prediction, and if the prediction is positive, an alert is given to the parent's mobile number so that they can contact the police and report the child's whereabouts.

2.2 Step I: Data collection and dataset preparation

In this phase, we collect data on facial expressions so that we can present the full range of feelings seen by the camera. All data fed into a CNN-based system must first be transformed into features [3] before they can be used effectively. Noise suppression, feature extraction, and data normalisation are all components of the pre-processing stage.

2.3 Dataset Description

For the proposed Internet of Things-based child safety alert model, it is necessary to use examples drawn from the Kaggle dataset. In this case, the dataset contains over 10k photos categorised in various ways. In addition, bounding boxes for anywhere between 4,000 and 5,000 images are provided for use in conducting object detection. Where and how many photos were taken for each of two or three kinds of mystery activity detection.

2.4 Step II: Developing a Machine Learning Algorithm for Facial Expression detection

The HUADM machine learning algorithm is used to determine a face expression. In order to construct a robust classifier, a time series format was chosen for the generated data. Moreover, it has powerful generalisation skills that allow it to classify freshly arriving data.

2.5 Child safety alert model using Yolov4:

The suggested IoT kid safety warning model uses the YOLOv4 to locate an area in an input photograph. The YOLO classifier is one of the deep learning-based networks used for object detection and categorization in the input photos[4]. Object detection pinpoints the precise position of an object by using the bounding boxes of the object as they appear in the input image. In this case, we use the YOLO-V4 classifier, which has been shown to be more accurate than previous YOLO classifiers. Additional semantic data can be gleaned from the input activity images by the YOLO-V4 during the training phase. Training the YOLO-V4 takes longer, but the increased detail over the previous feature map is worth the extra effort. That means the YOLOv4's tiniest objects will benefit from the boost in performance. Finally, after YOLOv4 has identified the mysterious behaviour in the input photos, it extracts the deep features from those images.

2.6 Extraction of Deep Features from Detected Unknown Activity:

Features of the photos that have been discovered are extracted $mg_m^{\det}$ CNN is used in the proposed model for identifying and classifying activities. Using detection images, CNN can pull out features for training $mg_m^{\det}$ and separates these features using the convolutional layer's hidden neurons' feature map. Here, the feature map provides identical weights to all neurons with the same feature map, while providing different weights to neurons with different feature maps. According to Eq (1).

$$O_c = af\left(Fe_c * mg_m^{\det}\right) \ldots\ldots\ldots\ldots(1)$$

The terms $mg_m^{\det}$ a Fe_c Definitions for "input images" and "convolution filter in the output feature map" are provided below. Each filter model in the input features is calculated using the 2D convolution filter. The activation function, denoted by, is used to extract the non-linear characteristics. The pooling layer then takes the spatial inconsistencies from the input noise and adds them to the feature map, lowering the resolution of the spatial map. In Eq., the maximum receptive field value is represented by the maximum number of features acquired in the pooling layer (2).

$$(OP)_{cst} = \max_{(x,y)\in T_{st}} \left(mg_m^{\det}\right)_{cxy} \ldots\ldots..(2)$$

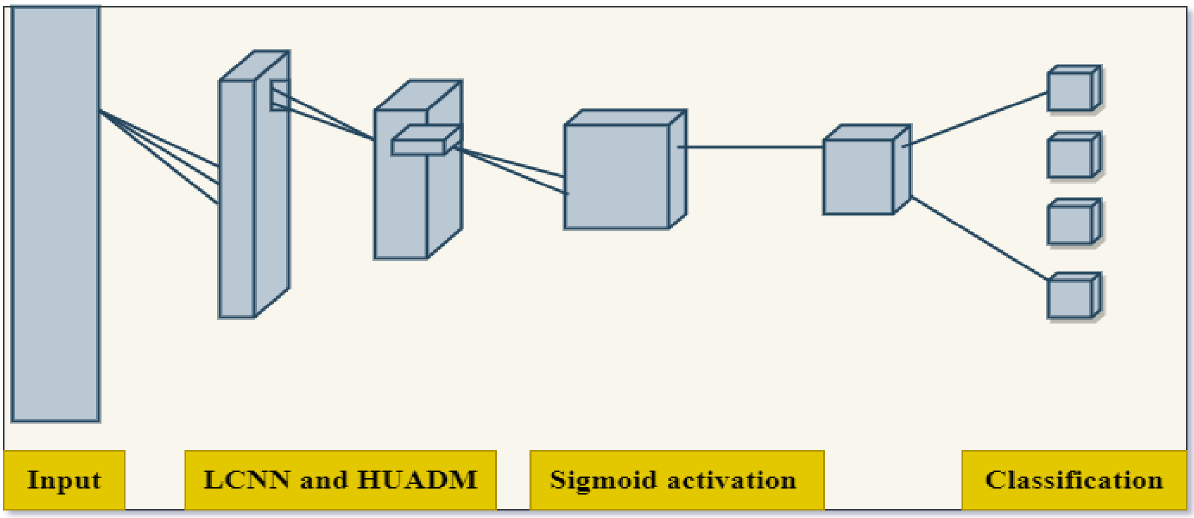

Figure 3: Detection of Unknown Activity: Extraction of Deep Features

Optimization of unlabeled activity classification using the Internet of Things with a modified LCNN network

2.7LCNN model

To prevent false positives while applying the best activity categorization model recommended by the Internet of Things, the proposed LCNN method utilises the retrieved features to categorise photos. By accelerating the classification stages, the recurrent structures of the deep learning algorithm eliminate the need to temporarily store the results in external memories. The recurrent design used by LSTM classifiers makes them more efficient computationally. "cells," "input gate," "output gate," and "forget gate" are the four parts of the LSTM network. The information from the cell was transferred to the input and output gates. The initial data sent by the network is calculated using the forget gate, as demonstrated in Eq (3).

$$c_t = \sigma\left(B_c \cdot \left[k_{t-1}, \left(FT_f^{ext}\right)_t\right] + w_c\right) \ldots\ldots\ldots\ldots (3)$$

Here, we display the results of the sigmoid activation function and the hidden respect algorithm. An input variable and details on the weight matrices are provided. The output of the cell, the output gate, and the forget gate are then each represented by their own symbols. The skewed values produced by these gates are demonstrated. You may read about the input gate in Eq (4).

$$g_t = \sigma\left(B_g \cdot \left[k_{t-1}, \left(FT_f^{ext}\right)_t\right] + w_f\right) \ldots\ldots\ldots\ldots\ldots (4)$$

The LSTM classifier uses a sigmoid activation function, which is shown as a hyperbolic tangent. At last, the created LCNN strategy yields categorised results for the proposed unknown activity identification, warning, and classification model.

2.8Proposed Hybrid unknown activity detection model (HUADM)

Using the proposed HUADM for optimising the hidden neurons of LSTM to enhance classification accuracy, a model for detecting and identifying and classifying activity has been developed. Given its high convergence rate and low time need, the hybrid technique was opted for in the suggested identification and classification model. Increased exploratory power is a byproduct of the large population variety that underpins the entire discovery procedure. Yet, there are other real-world scale optimization difficulties that must be fixed. As a result, the difficulties currently faced by the field are addressed by enhancing the proposed HUADM algorithm. The proposed HUADM uses a new fitness-based idea to calculate random variables s, improving the convergence performance of the algorithm.

$$rr = \frac{\left(a - (a-5)\right) * (1-0)}{\left[(a+5) - (a-5)\right]} + 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

$$a = \alpha * \frac{bestfit}{worstfit} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Variables in the suggested method, s, are selected using the fitness idea, but in the standard approach, these selections are made at random, hence the notation. The highest and worst fitness values are denoted by the terms and, respectively. The algorithm's population of solutions can be calculated with Eq (7).

$$pP = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1d} \\ y_{21} & y_{22} & \cdots & y_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{md} \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Algorithm 1: Proposed HUADM

Perform a population initialization using the parameters.
while(itr<=itr_{mx})
    upgrade the decreasing factor
for(in=1 to pP)
Compute the intensity S_m
Determine the random variable rr using Eq. 5
If(rr<0.5)
    updating the position of the solution
Else
    updating the position of the solution
Else If
    validate new position and set to the fitness fn_{new}
If(fn_{new}<=fn_{in})

Declare (y_m<=y_{new})and(fn_{in}<=fn_{new})
End If
If(fn_{new}<=fn_{pry})
Declare (y_{pry}<=y_{new}) and (fn_{pry}<=fn_{new})
End If
End for
End while
Return the best and most optimal solution End

2.9Modified CNN-LSTM model

The purpose of the proposed IoT-based activity classification model is to improve classification performance while simultaneously reducing the amount of time spent in training. To accomplish this, the model develops a hybrid deep learning approach known as LCNN by optimising the hidden neurons of LSTM with the HUADM algorithm. CNN is able to evaluate the high-level features based on statistical learning in order to enhance prediction accuracy even when presented with a massive volume of data. Comparatively speaking, LSTM outperforms other sequence learning algorithms in a variety of applications. This is due to the fact that it is used to circumvent the vanishing gradient problem and guarantees relative insensitivity to gap length. A boosted and hybrid version of CNN and LSTM codenamed LCNN is built in order to increase the performance of the suggested optimal activity classification model in feature extraction and classification. This is accomplished by constructing an LCNN. The optimal activity categorization model that was given has a goal function called the aim function, and its aim function is to maximise the accuracy that is stated in Eq (8).

$$FF = \underset{\{HN_b^{lstm}\}}{\arg\min}\left(\frac{1}{accy}\right) \text{…………………..(8)}$$

2.4 Step III: Experimental setup

The detection and classification model for unexplained activities was developed on the Python platform, and experimental analysis was utilised to evaluate the model's efficacy in detecting and classifying these events. In order to determine how well the suggested model works, the experimental inquiry contrasted it with advanced meta-heuristic algorithms and classifiers. This allowed the effectiveness of the model to be evaluated. An experimental examination with a population size of ten and a maximum of fifteen iterations was carried out for the proposed identification and classification model. Other deep learning methods, including convolutional neural networks, recurrent neural networks, and long short-term memory, were evaluated alongside the suggested technique.

2.10Performance metrics

Following are a number of quantitative indicators used to assess the effectiveness of the proposed activity identification and classification model.

(a) In Eq. 1, FPR is defined as "the ratio between the numbers of negative events mistakenly classified as positive (false positives) and the total number of actual negative events" (9).

$$F_{pr} = \frac{F^p}{F^p + T^n} \text{………………(9)}$$

(b) Specificity S_{spcty} is "the proportion of negatives that are correctly identified," as represented in the Eq. (10)

$$S_{spcty} = \frac{T^n}{T^n + F^p} \text{…………………(10)}$$

(c) Sensitivity $S_{senstvy}$ is "the proportion of positives that are correctly identified," as denoted in Eq. (11)

$$S_{senstvy} = \frac{T^p}{T^p + F^n} \text{………………(11)}$$

3.Result and Discussion:

3.1 Analysis of classifiers applied to the proposed model based on the best possible activity categorization
The developed HUADM-LCNN is used to assess the performance of the suggested unknown activity identification and classification model with a number of different classifiers at a number of various learning percentages, as given in Table. At a learning rate of 65, the suggested method produces higher MCC values compared to the CNN, RCNN, and LSTM.

Table 1: Analysis of the suggested activity identification and classification model in comparison to previously used classifiers

Measures	CNN	RCNN [5]	LSTM [2]	HUADM-LCNN
"Accuracy"	0.779958	0.794595	0.794897	0.875122
"Sensitivity"	0.779536	0.794293	0.204672	0.890011
"Specificity"	0.780382	0.794897	0.79481	0.882365
"Precision"	0.780779	0.795328	0.58919	0.881309
"FPR"	0.219618	0.205103	0.205902	0.121108
"FNR"	0.220464	0.205707	0.20491	0.121197
"FDR"	0.219221	0.79509	0.205142	0.888812
"F1-score"	0.780157	0.794098	0.794974	0.888992
"MCC"	0.559917	0.794858	0.589188	0.889308

Using this classifier analysis, we find that the suggested method not only achieves better results across the board quantitatively but also achieves a significantly lower error rate. Consequently, compared to traditional classifier approaches, the suggested activity identification and classification model's implementation of HUADM-LCNN yields superior performance. The suggested activity detection and classification model thus outperforms the state-of-the-art techniques.

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