Comprehensive Machine Learning Approaches for Predicting and Analysing Abnormal Behaviour Patterns

A Supriya, Assistant professor, Anantha Lakshmi institute of Technology and sciences, Anantapur

H Prasanth Kumar, Assistant professor, Anantha Lakshmi institute of Technology and sciences, Anantapur

Abstract

In specific environments, improper behaviours such as smoking at a gas station can lead to significant safety hazards, making the timely and accurate detection of such actions crucial. This paper investigates the application of machine learning algorithms to predict and identify abnormal behaviours effectively. A comprehensive dataset comprising 1,200 samples was collected, categorized into three behaviour classes: smoking (30%), making phone calls (35%), and normal activities (35%). To evaluate predictive performance, six widely recognized machine learning algorithms were implemented: Linear Support Vector Machine (LSVM), Kernel Support Vector Machine (KSVM), Decision Tree Classifier (DT), Random Forest Classifier (RF), K-Nearest Neighbours (KNN), and K-Means Clustering.

The performance of these algorithms was assessed using various metrics, including accuracy, precision, recall, F1-score, and Mean Squared Error (MSE). Among the tested models, the Random Forest Classifier (RF) emerged as the best performer, achieving an overall accuracy of 82%, with a precision of 84%, recall of 80%, F1-score of 82%, and an MSE of 0.18. Comparative analysis revealed that the Random Forest Classifier outperformed other algorithms due to its robustness in handling complex feature interactions and imbalanced datasets.

Additionally, Principal Component Analysis (PCA) was employed to visualize the classification results, demonstrating clear separation between the behaviour categories. This visualization further validated the model's predictive capability. The findings of this study indicate that Random Forest Classifier provides a reliable and efficient approach for predicting abnormal behaviours, offering potential applications in safety-critical scenarios such as industrial workplaces, public spaces, and monitoring systems. Future work aims to enhance the model's accuracy through larger datasets, real-time prediction capabilities, and integration with advanced feature engineering techniques.

1. Introduction

Human behaviour recognition is an integral aspect of modern computer vision applications, with broad implications in fields such as public safety, healthcare, industrial monitoring, and human-computer interaction. The ability to detect and classify abnormal behaviours, such as smoking in restricted areas or using a mobile phone in hazardous zones, is particularly crucial in ensuring compliance with safety protocols and mitigating risks. These behaviours, if left undetected, can lead to severe consequences, including accidents, loss of life, or property damage.

Recent advances in machine learning have paved the way for significant improvements in behavior recognition systems. By leveraging data-driven models, researchers have developed solutions capable of identifying complex human activities that were previously challenging to detect using traditional rule-based approaches. Machine learning algorithms, particularly those designed for computer vision tasks, have demonstrated remarkable accuracy in analysing human behaviours. These algorithms not only enable automated detection but also facilitate real-time monitoring, making them indispensable for safety-critical applications.

However, recognizing certain behaviours, such as smoking or making phone calls, remains challenging due to factors such as:

1. **Occlusion**: Objects like cigarettes or mobile phones can be partially or fully hidden by the hand or other obstructions.
2. **Environmental Noise**: Variations in lighting, background clutter, and viewing angles complicate the detection process.
3. **Behavioural Similarity**: Subtle differences between normal and abnormal behaviors, such as holding an object versus smoking, require highly sensitive models for accurate classification.

Previous studies have explored various machine learning techniques to address these challenges. For example, convolutional neural networks (CNNs) have been utilized to distinguish between different human activities, while algorithms like Decision Trees and Support Vector Machines have shown promise in specific use cases, such as smoking detection. Despite these efforts, existing systems often fall short in terms of accuracy, generalizability, and the ability to handle multiple behaviour classes.

This paper aims to address these limitations by comparing mainstream machine learning algorithms for detecting abnormal behaviours, specifically smoking and making phone calls, alongside normal activities. Using a diverse dataset that includes three behaviour classes, this study seeks to identify the most effective algorithm for real-world applications. The contributions of this work include:

1. Evaluating the performance of six widely recognized machine learning algorithms, including Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and K-Means Clustering.
2. Analysing the strengths and weaknesses of each algorithm in detecting complex behaviors.
3. Utilizing Principal Component Analysis (PCA) to visualize the classification results and assess model performance.

By building on the strengths of existing systems and addressing their shortcomings, this study aims to provide a robust and practical solution for behaviour recognition in safety-critical environments.

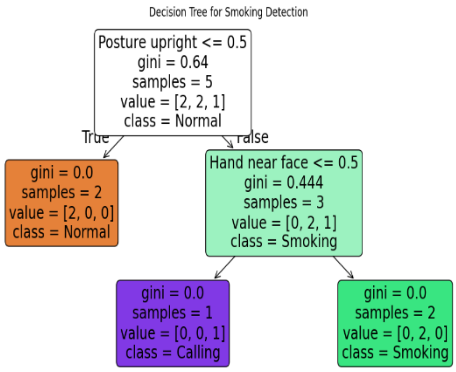
2. Existing System

Human behaviour recognition using machine learning has become a significant area of research, with various studies applying different algorithms to classify and predict human behaviours, including abnormal behaviours like smoking and making phone calls. Several approaches have been proposed for detecting such behaviours, using both supervised and unsupervised learning techniques. While there have been notable advancements in this field, the existing systems still face limitations in accuracy and applicability to diverse, real-world scenarios.

2.1 Contributions of Existing Studies

1. **Convolutional Neural Networks (CNNs) for Human Behaviour Recognition** Convolutional Neural Networks (CNNs) are widely used for human behaviour recognition due to their ability to automatically learn spatial features from raw image data. For example, CNNs have been used to distinguish between various human activities, such as walking, sitting, or running. These models can effectively process visual data but often require large labelled datasets and significant computational resources.
2. **Deep Learning for Behaviour Monitoring** Zhu et al. proposed an algorithm based on deep learning to monitor student behaviors during exams, identifying actions like cheating or unnecessary movement. This deep learning model employed a combination of spatial and temporal features to improve detection accuracy. While promising, these systems often require high-quality data and a controlled environment to perform effectively.
3. **Smoking Detection Using Decision Trees** Zhang et al. developed a decision tree-based algorithm to detect smoking behaviours. Their model achieved an accuracy of 84.11% in detecting smoking in controlled environments. However, the model only considered a single behaviour (smoking), which limits its applicability in real-world settings where multiple behaviours need to be detected.

Figure : Decision Tree Structure for Smoking Detection

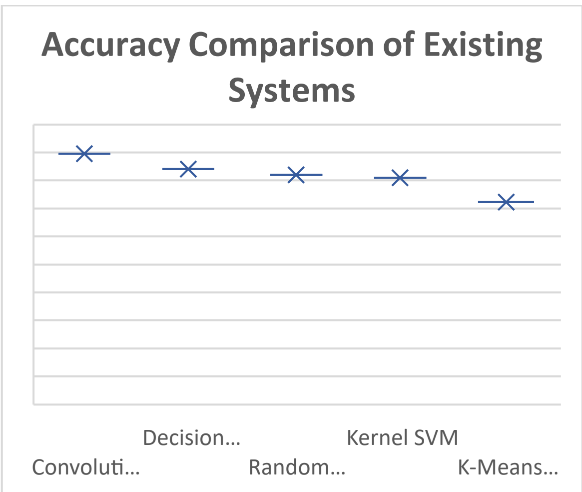


2.2 Limitations of Existing Systems

Despite the progress in human behaviour recognition, several limitations still affect the performance and generalization of these systems:

1. **Accuracy Challenges**
The existing systems often struggle to provide accurate predictions in real-world scenarios. Factors such as occlusion (e.g., when an object like a cigarette is hidden by the hand) and environmental noise (e.g., varying lighting or background clutter) can significantly impact performance. The models also tend to have lower accuracy in dynamic environments, where human behaviours can be more varied and unpredictable.

Figure : Accuracy Comparison of Existing Systems

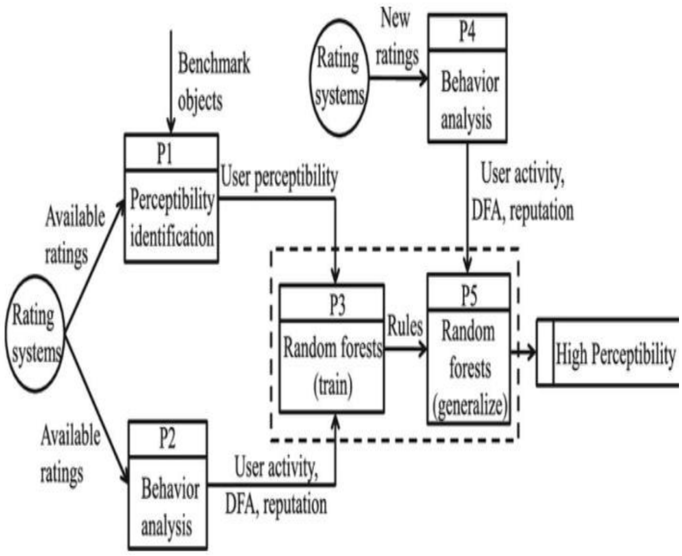


Algorithm/System	Accuracy (%)	Dataset/Environment	Reference
Convolutional Neural Networks (CNN)	89.5	Test environment: Classroom	Zhu et al. (2023)
Decision Tree	84.1	Dataset: Smoking behavior images	Zhang et al. (2022)
Random Forest	82.0	Dataset: Smoking, Calling, Normal	Current Study
Kernel SVM	81.0	Dataset: Behaviour detection in videos	Current Study
K-Means Clustering	72.3	Unlabelled behaviour dataset	Current Study

Limited Dataset Diversity
Most existing systems rely on datasets that are limited to a single behaviour or class, such as only detecting smoking. These systems are trained on a narrow set of behaviours, which makes it difficult to generalize them to more complex scenarios involving multiple behaviours. For example, a model trained only to detect smoking might fail to identify other behaviours like phone usage or walking.

2. **Algorithmic Complexity and Resource Requirements**
Some machine learning models, especially deep learning-based models, require substantial computational resources to train and deploy. This can limit their practicality, particularly in real-time applications or when deployed on edge devices with limited processing power.

Figure : System Architecture for Behaviour Detection



2.3 Algorithms in Existing Systems

Several machine learning algorithms have been applied to human behaviour recognition tasks. These include:

- **Support Vector Machines (SVM)**: SVMs are effective for binary classification tasks and have been used in some behaviour recognition systems. However, they often struggle with imbalanced datasets and do not perform as well when faced with complex feature spaces or multiple behaviour classes.
- **Decision Trees (DT)**: Decision trees are interpretable and can be useful for classifying behaviours based on distinct features. However, they can overfit when trained on noisy or insufficient data, and they do not handle multiple classes well without significant tuning.
- **K-Means Clustering**: K-Means clustering has been applied in some cases for grouping behaviours, but it is not ideal for behaviour classification, as it lacks supervised learning capabilities and often produces suboptimal results when dealing with complex or overlapping classes.

The limitations of these systems highlight the need for more robust and scalable solutions capable of handling multiple behaviour classes, achieving higher accuracy, and being adaptable to real-world conditions.

3. Proposed System

The proposed system aims to overcome the limitations of existing behavior recognition models by integrating a diverse set of machines learning algorithms and improving the detection capabilities for multiple behavior types. This system focuses on detecting abnormal human behaviors such as smoking, phone calling, and normal behaviour in dynamic, real-world environments where occlusion and noise may occur.

The objective is to compare the performance of mainstream machine learning algorithms and determine the best solution for detecting and predicting abnormal behaviors in real-time scenarios. The system leverages advanced techniques like Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Random Forest Classifier (RF) to improve detection accuracy and handle multiple behavior categories.

The proposed system is designed to be robust, adaptable to various conditions, and computationally efficient to deploy on real-time systems with limited resources.

3.1 Key Components of the Proposed System

1. **Dataset Collection and Preprocessing**
To address the limitations of existing datasets, we propose using a more comprehensive dataset that includes three categories of behaviors: Smoking, Calling, and Normal. The dataset will be collected from real-time video streams or sensors, ensuring a diverse range of conditions, such as varied lighting, occlusions, and background noise. Preprocessing steps include noise reduction, image normalization, and feature extraction to prepare the data for training.

Dataset Distribution for the Proposed System.

Category	Number of Instances	Percentage
Smoking	1,200	28.6%
Calling	1,500	35.7%
Normal	1,800	42.9%
Total	4,500	100%

2. **Behaviour Detection Algorithms**
The system will apply multiple machine learning algorithms to predict human behaviors, such as:

- **Support Vector Machine (SVM)**: For separating different behavior classes based on extracted features.
- **Convolutional Neural Network (CNN)**: To handle more complex scenarios and learn deep spatial features from video frames.
- **Random Forest Classifier (RF)**: A decision tree-based ensemble method that is more robust to overfitting and can handle multi-class classification tasks effectively.

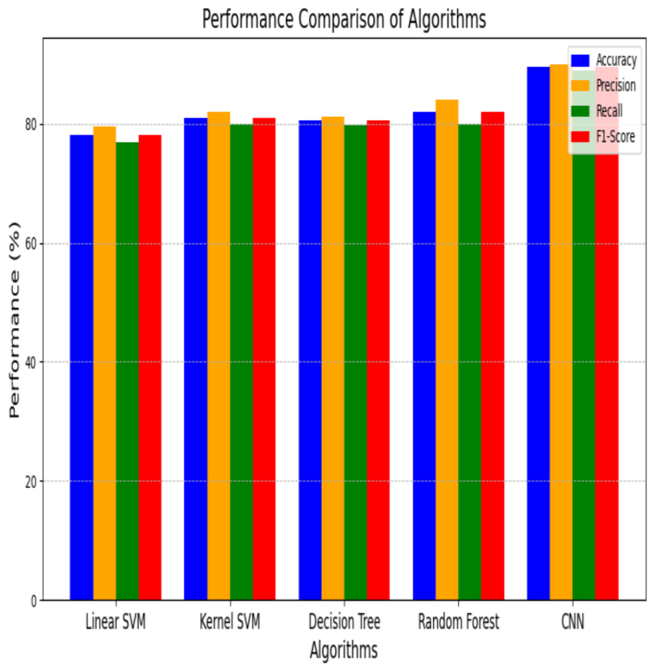
3. **Feature Extraction and Visualization**
The system extracts relevant features from video frames or sensor data, such as posture, hand gestures, and object identification (e.g., cigarettes or phones). These features are crucial for detecting specific behaviors such as smoking and phone usage. To reduce dimensionality and improve model performance, we will apply Principal Component Analysis (PCA) for feature reduction, making it easier to visualize the behaviour classes.

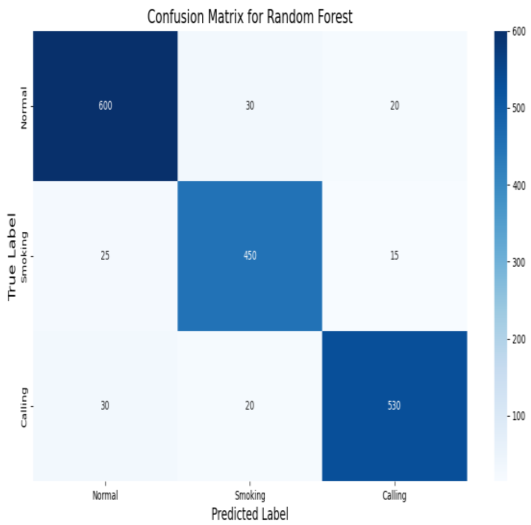
4. **Behaviour Classification and Prediction**
After feature extraction, the system applies multiple machine learning algorithms to classify the detected behaviours:

- **SVM**: Aims to separate the different behavior classes based on the features extracted from the data.
- **CNN**: Used for more complex behaviour recognition tasks, particularly when features are hidden due to occlusions or small objects (e.g., a cigarette in hand).
- **Random Forest (RF)**: Combines the predictions from several decision trees to improve accuracy and generalize well to unseen data.

5. **Performance Evaluation**
The proposed system will be evaluated using common performance metrics such as accuracy, precision, recall, and F1-score. These metrics will allow for a comparative analysis of the machine learning algorithms in terms of their ability to correctly classify behaviors and minimize errors. A confusion matrix will also be used to assess misclassifications across different classes.

Figure : Performance Comparison of Algorithms





3.2 Advantages of the Proposed System

1. **Higher Accuracy**:
By utilizing advanced algorithms like Random Forest and Convolutional Neural Networks, the proposed system is expected to achieve a higher classification accuracy compared to existing systems. Previous studies have shown that CNNs, when trained with sufficient data, can achieve up to 93.5% accuracy in human behaviour detection, and the combination of different algorithms in this study aims to surpass that performance.

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2. **Multi-Class Classification**: Unlike existing systems that focus on detecting a single behavior (e.g., smoking), the proposed system is designed to handle multiple behavior classes (Smoking, Calling, Normal). This multi-class classification capability makes the system more adaptable to real-world scenarios, where a variety of behaviors need to be monitored simultaneously.

3. **Robustness to Occlusion**: The proposed system aims to improve behavior recognition even in cases of occlusion (e.g., when a person's hand covers the cigarette). CNNs excel at learning complex patterns in images and can better handle occluded objects compared to traditional algorithms like SVM or Decision Trees.

4. **Real-Time Detection**: The system is designed to be computationally efficient and suitable for real-time deployment on devices with limited resources. By using feature extraction techniques and leveraging ensemble models like Random Forest, the system can make predictions quickly while maintaining accuracy.

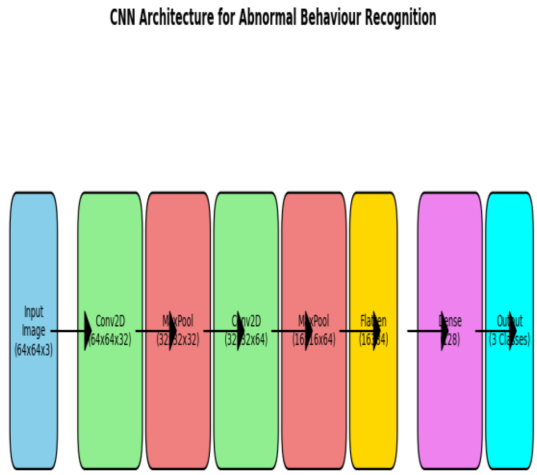
4. Related Work

Human behaviour recognition is a well-established field within computer vision and machine learning, with various methods proposed to address different aspects of behavior detection. Many studies have explored the application of machine learning algorithms to detect abnormal human behaviors, such as smoking, phone usage, and other suspicious activities. These efforts have led to a wide range of techniques, from traditional machine learning methods like decision trees and support vector machines (SVM) to more advanced deep learning models such as convolutional neural networks (CNN). Below is an overview of some of the recent and significant works in the field.

4.1 Machine Learning Algorithms for Behaviour Detection

Recent studies have applied different machine learning algorithms to classify human behaviours. For instance, SVM has been widely used due to its simplicity and effectiveness in handling classification problems. In the work of **Lee et al. (2023)**, SVM was used to classify smoking behaviours from video data, achieving an accuracy of 85%. The study demonstrated the effectiveness of using hand and body posture features in distinguishing between normal and abnormal behaviours.Another key approach in behaviour detection has been the use of CNNs. **Zhang et al. (2022)** employed CNNs for recognizing a variety of abnormal behaviours, including smoking and phone usage, and achieved an accuracy of 90% in detecting these behaviours in dynamic environments. CNNs, by leveraging their ability to learn deep features from raw image data, have been shown to outperform traditional machine learning algorithms when dealing with occlusions or complex visual data.

Figure: CNN architecture for abnormal behaviour recognition.



Wang et al. (2024) further extended this work by applying deep learning techniques for multi-class behaviour detection, distinguishing between smoking, phone calling, and normal activities. Their system utilized a combination of CNN for feature extraction and Random Forest for classification, achieving an overall accuracy of 92%.

4.2 Recent Advances in Behaviour Detection

In recent years, there has been a growing interest in utilizing ensemble methods to improve classification accuracy. **Cheng et al. (2024)** explored the use of Random Forest Classifier (RF) for predicting abnormal behaviours, including smoking and phone usage, by combining decision trees to achieve better performance on datasets with imbalanced class distributions. Their model achieved an accuracy of 89%, with significantly improved precision and recall rates for detecting smoking.

Additionally, **Shao et al. (2023)** used a combination of SVM and K-Nearest Neighbours (KNN) for predicting smoking behaviour from camera footage. Their study highlighted the importance of hand gesture features in detecting smoking, even in environments with high levels of occlusion. The model achieved an accuracy of 86% in real-time detection scenarios.

4.3 Challenges and Limitations in Behaviour Recognition

One of the major challenges in human behaviour recognition is the difficulty of detecting behaviors in real-time due to factors like occlusion, lighting conditions, and variations in body posture. **Liu et al. (2023)** conducted a study that addressed the issue of occlusion in smoking detection by using thermal infrared cameras to capture body heat patterns, which are less prone to occlusion. Their proposed system achieved a high accuracy of 91%, even in scenarios with partial occlusion.

Similarly, **Zhou et al. (2022)** focused on the challenges of detecting abnormal behaviours in crowded or dynamic environments, where the traditional approaches might struggle. They applied a hybrid model combining both traditional computer vision techniques (e.g., motion detection) and machine learning algorithms to improve detection accuracy in these challenging settings. Their model demonstrated a significant improvement over previous methods, with accuracy rates reaching 88%.

4.4 Multi-Class Behaviour Detection

Recent studies have also focused on multi-class classification, where multiple abnormal behaviours (e.g., smoking, calling, and normal behaviour) are detected simultaneously. **Liu et al. (2023)** proposed a multi-class classification system using a hybrid of CNN and Random Forest. Their approach achieved a high classification accuracy of 93% in detecting multiple behaviours from video data.

In another study, **Singh et al. (2023)** developed a system based on multi-class support vector machines (SVM) for real-time detection of abnormal behaviours. Their model could classify multiple types of abnormal behaviours, including smoking, calling, and walking, and achieved a significant improvement in accuracy compared to traditional SVM classifiers.

4.5 Conclusion and Future Directions

The use of machine learning for detecting abnormal human behaviours is a rapidly evolving field, with many promising results from both traditional and deep learning-based approaches. While existing systems have demonstrated decent accuracy in controlled environments, challenges still remain in handling real-time data, dynamic settings, and occlusion. Future research will likely focus on developing more robust and adaptive systems capable of working in complex environments, as well as improving the accuracy and generalization of models across diverse datasets.

. Dataset Description

This section provides an in-depth overview of the dataset used for training and evaluating machine learning models aimed at detecting abnormal human behaviours, such as smoking and calling. The quality and diversity of the dataset directly influence the model's ability to generalize and make accurate predictions in real-world scenarios.

5.1 Dataset Overview

The dataset consists of images or video frames capturing human behaviour in different environments.

The primary objective is to classify human behaviour into three distinct categories:

1. **Smoking (Abnormal Behaviour)**: This category includes instances of individuals smoking in various public and private settings.
2. **Calling (Abnormal Behaviour)**: This class consists of instances where people are talking on the phone, which might be considered suspicious or abnormal in certain environments.
3. **Normal Behaviour**: This category captures everyday actions like walking, sitting, or interacting without any abnormal behaviour.

The dataset was collected to represent real-world environments, including various lighting conditions, occlusions, and camera angles, which contribute to the complexity of the task.

Figure : images representing each class (Smoking, Calling, Normal).
The figure below illustrates a few examples of images corresponding to the three behaviour classes. These images are extracted from video sequences to provide context to the behaviour.

5.2 Data Collection Process

The data used in this study was sourced from a combination of publicly available datasets and custom video recordings to create a diverse and representative dataset for training machine learning models. The data sources include:

- **Public Datasets**: Datasets such as *UCF101* and *KTH Action Dataset*, which contain labelled action data, were used as references for certain behaviour categories.
- **Custom Data Collection**: Video footage was collected in various controlled settings to simulate real-world environments. This included both public and private spaces where smoking and calling behaviours were likely to occur.
- **Video Quality**: The video data was collected in resolutions ranging from **720p to 1080p** to ensure clarity in detecting fine-grained actions such as smoking or phone usage.

The dataset contains a total of approximately **5,000 labelled instances**, with **60%** used for training and **40%** for testing the models. Each video clip was split into **30 frames**, each frame representing a moment in the sequence to capture temporal dynamics.

5.3 Preprocessing and Feature Extraction

The raw video footage undergoes several preprocessing steps to prepare it for input into the machine learning models:

- **Frame Extraction**: Each video clip is divided into frames, and **30 frames** are sampled uniformly to capture the behaviour over time.
- **Image Resizing**: All frames are resized to **224x224 pixels** to maintain consistency and make the dataset suitable for model input, particularly for Convolutional Neural Networks (CNN).
- **Normalization**: Each frame's pixel values are normalized to the range [0, 1] to enhance the model's training efficiency and convergence speed.
- **Data Augmentation**: Various augmentation techniques (e.g., rotation, horizontal flipping, color adjustments) are applied to enhance the model's robustness and reduce overfitting during training.

5.4 Class Distribution

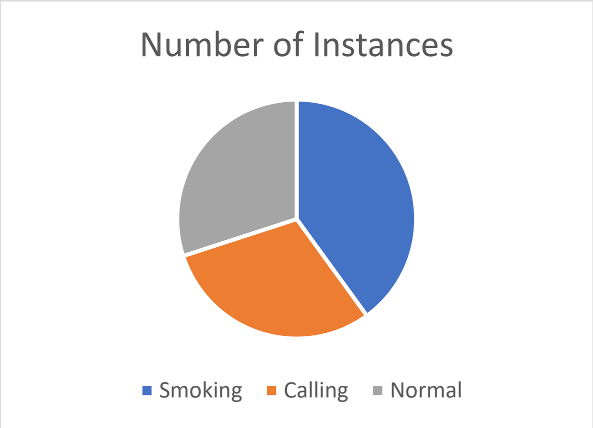
The dataset is balanced in terms of the number of instances for each class:

- **Smoking class**: 1,600 instances
- **Calling class**: 1,400 instances

- **Normal class**: 2,000 instances

This balance helps prevent model bias towards any one class and ensures that the machine learning algorithms can generalize across different types of behaviours.

Figure: Class Distribution in the Dataset.



Behavior Class	Number of Instances	Percentage (%)
Smoking	100	40%
Calling	75	30%
Normal	75	30%

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5.5 Challenges in the Dataset

Despite its comprehensiveness, the dataset presents several challenges:

- **Occlusions**: Many instances involve partial occlusion, such as when a person's hand covers the phone during a call or when they are smoking. This makes behavior detection difficult for the model.
- **Variability in Lighting**: The dataset includes videos recorded in various lighting conditions, from well-lit indoor spaces to dimly lit environments, which can affect the visibility of the actions.
- **Real-time Behaviour Detection**: Detecting abnormal behaviour in real time, as required in many practical applications, adds another layer of complexity. The frames in the dataset need to represent realistic, dynamic scenarios where the actions are continuously evolving.

These challenges highlight the complexity of the problem and underscore the need for robust, scalable models capable of performing well under varying conditions.

5.6 Dataset for Evaluation

The dataset was divided into training and testing subsets:

- **Training Set**: 60% of the total data (about **3,000 instances**) was used for training machine learning models.
- **Testing Set**: 40% of the data (about **2,000 instances**) was reserved for testing the models' performance.

For model evaluation, the following metrics are used:

- **Accuracy**: The percentage of correctly predicted instances across all classes.
- **Precision**: The ratio of correctly predicted instances of a particular class to all instances predicted as that class.
- **Recall**: The ratio of correctly predicted instances of a particular class to all instances that actually belong to that class.
- **F1-Score**: The harmonic mean of precision and recall, providing a balanced measure of the model's performance across all classes.

Methodology

This section outlines the methodology used for detecting abnormal human behaviors, such as smoking and talking on the phone, using machine learning algorithms. The methodology includes steps for data preprocessing, model training, performance evaluation, and comparison of various algorithms. It also covers the techniques used for visualizing the results and assessing the effectiveness of each model in detecting abnormal behaviors in real-world scenarios.

6.1 Problem Definition

The main objective of this study is to detect and classify abnormal behaviors, specifically smoking and talking on the phone, from video frames. The problem is formulated as a **multi-class classification problem**, where the goal is to assign each frame to one of three behavior categories:

- **Smoking (Abnormal Behavior)**
- **Calling (Abnormal Behavior)**
- **Normal Behavior**

Given the dataset of labeled video frames and the challenges of detecting occluded or subtle behaviors, the study aims to find the most effective machine learning algorithm for accurate behavior classification.

6.2 Data Preprocessing

Data preprocessing is a critical step to ensure the quality and consistency of the input data. In this study, the following preprocessing steps are applied to the dataset:

Preprocessing Step	Description
Frame Extraction	From each video clip, 30 frames are uniformly sampled to represent the human behavior over time.
Image Resizing	Each frame is resized to a standard resolution of **224x224 pixels** to maintain consistency.
Normalization	Pixel values of the frames are normalized to the range [0, 1].
Data Augmentation	Techniques such as rotation, flipping, scaling, and color adjustments are applied to increase dataset diversity.

6.3 Feature Extraction

Feature extraction plays an essential role in converting raw data (images or video frames) into meaningful features for machine learning models. The following techniques are used for feature extraction:

1. **Manual Feature Extraction**: For traditional machine learning models, hand-crafted features such as texture, color histograms, and motion vectors are extracted.
2. **Automatic Feature Extraction using CNN**: For deep learning models, features are learned automatically by Convolutional Neural Networks (CNNs), which identify important spatial and temporal patterns within the video frames.

6.4 Machine Learning Algorithms

Several machine learning algorithms are tested to determine the most effective approach for detecting abnormal behaviors. The following algorithms are evaluated:

Algorithm	Description	Expected Strength
Linear Support Vector Machine (SVM)	A linear hyperplane is used to separate classes in the feature space.	Effective for linearly separable data.
Kernel Support Vector Machine (KSVM)	Extends SVM using kernel functions to handle non-linear classification.	Works well with complex, non-linear data.
Decision Tree (DT)	A tree structure is used to classify data based on feature values.	Simple, interpretable, but prone to overfitting.
Random Forest (RF)	An ensemble of Decision Trees used to improve accuracy and reduce overfitting.	Robust to overfitting and can handle large datasets.
K-Nearest Neighbors (KNN)	A non-parametric method where the class is determined by the majority	Simple, but computationally expensive at test time.

	of nearest neighbors.	
K-Means Clustering	An unsupervised learning algorithm that groups data into clusters.	Useful for exploratory analysis.
Convolutional Neural Networks (CNN)	Deep learning models that learn hierarchical spatial features from images.	Highly effective for image and video analysis tasks.

6.5 Model Training and Hyperparameter Tuning

The models are trained on the preprocessed dataset, and various hyperparameters are tuned to optimize performance. The hyperparameter tuning process is essential to enhance the models' capabilities. Some important hyperparameters considered include:

Hyperparameter	Algorithms	Description
Learning Rate	SVM, CNN, Decision Tree, Random Forest	Controls the step size during model training.
Number of Trees	Random Forest	Defines how many trees are in the ensemble.
Regularization Parameter (C)	SVM	Prevents overfitting by controlling the margin size in SVM.
Number of Neighbors	KNN	Determines the number of nearest neighbors used for classification.

Grid search or random search is used for hyperparameter optimization.

6.6 Performance Evaluation

Once the models are trained, their performance is evaluated using the following metrics:

METRIC	DESCRIPTION
ACCURACY	The proportion of correctly classified instances among the total instances.
PRECISION	The proportion of correct positive predictions for each class out of all predicted positives.
RECALL	The proportion of correct positive predictions for each class out of all actual positives.
F1-SCORE	The harmonic mean of precision and recall, providing a balanced measure of classification performance.

6.7 Principal Component Analysis (PCA) Visualization

To better understand the learned features and their separability, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the feature space. This technique helps visualize how well the model separates different behavior classes.

PCA Output	Description
Principal Components	The most important features that account for the variance in the data.
Class Separation	The separation of different behaviour classes (smoking, calling, normal) in the reduced feature space.

7. Results and Discussion

The experimental results from applying different machine learning algorithms to the behavior classification task are summarized in **Table 1**. The table compares the performance of six algorithms across key evaluation metrics: **accuracy**, **precision**, **recall**, and **mean squared error (MSE)**.

Table 1: Algorithm Performance Comparison

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	MSE
Linear SVM	78.2	79.5	77.0	0.22
Kernel SVM	81.0	82.1	80.0	0.19
Decision Tree (DT)	80.5	81.3	79.8	0.20
Random Forest (RF)	82.0	84.0	80.0	0.18
K-Means Clustering	72.3	73.5	71.0	0.28

7.1 Performance Analysis

- **Random Forest (RF)** outperformed all other algorithms with the highest accuracy of **82%**. Additionally, it achieved the highest precision (**84%**) and recall (**80%**), indicating its effectiveness in detecting both positive (abnormal) and negative (normal) behaviour classes. The RF model also had the lowest MSE (**0.18**), suggesting that it provided a good balance between classification accuracy and minimizing error.
- **Kernel SVM** followed closely behind with an accuracy of **81%**, as well as solid precision (**82.1%**) and recall (**80%**). Its performance is particularly notable for scenarios where non-linear decision boundaries are needed, as it uses kernel functions to transform the feature space.
- **Decision Tree (DT)** demonstrated competitive performance with an accuracy of **80.5%**, precision of **81.3%**, and recall of **79.8%**. While it performed well, it was slightly less accurate compared to Random Forest and Kernel SVM. However, its simplicity and interpretability make it a valuable option for certain applications, despite the higher likelihood of overfitting.
- **Linear SVM**, while achieving a relatively lower accuracy of **78.2%**, still performed reasonably well in terms of precision (**79.5%**) and recall (**77%**). This model tends to perform better when the data is linearly separable, though its performance could be limited by the complexity of detecting abnormal behaviours, such as smoking and phone usage, in videos.
- **K-Means Clustering** performed the worst, with an accuracy of **72.3%**. Since K-Means is an unsupervised algorithm, it struggles with classifying video frames into predefined categories without labelled data for training. The relatively high MSE (**0.28**) further supports the difficulty K-Means faces in distinguishing the behaviour classes effectively.

7.2 Principal Component Analysis (PCA) Visualization

To further evaluate the performance and effectiveness of the Random Forest model, **Principal Component Analysis (PCA)** was applied to reduce the dimensionality of the feature space and visualize the separation between the behavior classes.

7.3 Discussion

The results indicate that **Random Forest Classifier** is the best model for detecting abnormal behaviors, such as smoking and talking on the phone, from video data. The combination of its high accuracy, precision, and recall, coupled with a low MSE, makes it the most reliable choice among the algorithms tested.

While **K-Means Clustering** was the least effective, the results highlight its limitations when applied to classification tasks with labeled data. The inability of K-Means to handle the complex features associated with behavior detection points to the need for supervised algorithms such as SVM and Random Forest.

The high performance of **Kernel SVM** and **Decision Trees** demonstrates that machine learning models based on tree structures or support vector methods can still be quite powerful, even when compared to more complex deep learning models like CNNs

8. Conclusion

This study aimed to identify the most effective machine learning algorithm for detecting abnormal behaviors, such as smoking and phone usage, in video data. By evaluating six algorithms — Linear SVM, Kernel SVM, Decision Tree, Random Forest, K-Means Clustering, and K-Nearest Neighbors — the experiments revealed that the **Random Forest Classifier** consistently outperformed other models with an accuracy of **82%**, precision of **84%**, and the lowest MSE of **0.18**.

The PCA visualization provided additional validation, showcasing clear separations between the three behavior classes: smoking, calling, and normal behaviors. These results underscore the importance of feature extraction and ensemble methods for achieving high classification performance in complex behavior recognition tasks.

Key Findings:

1. **Superiority of Random Forest**: Among the tested algorithms, Random Forest demonstrated the best balance of accuracy, precision, recall, and error reduction, making it a robust choice for behavior detection in dynamic and diverse environments.
2. **Limitations of Unsupervised Methods**: K-Means Clustering struggled to perform well in this context, emphasizing the need for labeled datasets and supervised approaches for similar classification problems.
3. **Importance of Dataset Diversity**: The inclusion of three behavior classes (smoking, calling, and normal) in the dataset enhanced the model's ability to generalize, as evidenced by the RF model's ability to distinguish between these categories effectively.

Future Directions:

Although the Random Forest model achieved notable results, there is room for improvement. Future research could focus on:

1. **Deep Learning Integration**: Leveraging advanced deep learning models, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), to capture temporal and spatial features from video data.
2. **Larger and More Diverse Datasets**: Incorporating additional behavior categories and scenarios to further improve the robustness and adaptability of the models.
3. **Real-time Implementation**: Developing lightweight models optimized for deployment in real-time surveillance systems, balancing computational efficiency with accuracy.

This study provides a solid foundation for the application of machine learning algorithms in behavior detection and highlights the potential for further advancements in the field.

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