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Abstract—Yoga pose detection holds significant importance in various aspects of the yoga practice and its integration with technology. The importance of yoga lies in its ability to promote physical health, mental well-being, stress reduction, improved focus, emotional balance, resilience, spiritual growth, and a holistic approach to life. With the increasing popularity of yoga, there is a growing need for technological advancements to support practitioners and instructors in monitoring and refining their practice. The paper begins by outlining the significance of automated yoga pose detection, highlighting the potential benefits it offers in providing real-time feedback, enhancing self-correction, and optimizing performance. It explores the existing literature on computer vision and machine learning techniques applied to human pose estimation and their applicability to yoga pose detection. Based on a thorough review of state-of-the-art methodologies, the research paper proposes a yoga pose detection that combines multiple modalities, including RGB images, depth maps, and skeletal joint data. The proposed system leverages deep learning algorithms, such as convolutional neural networks (CNNs) and long short-term memory (LSTM), to precisely recognize and continuously monitor yoga poses. Moreover, the paper discusses the challenges associated with pose variation, occlusion, and complex body movements within yoga practice. It explores strategies for data augmentation, model optimization, and performance evaluation to ensure robustness and accuracy of the proposed detection system. The practical implications of the research are discussed, emphasizing the potential for widespread adoption of yoga pose detection systems in various settings, including yoga studios, fitness centers, and home practice environments. The paper concludes by outlining future research directions and the potential for integrating the proposed system with emerging technologies, such as augmented reality (AR) and virtual reality (VR), to enhance the yoga experience and facilitate remote instruction. Overall, this research paper contributes to the advancement of automated yoga pose analysis, offering a comprehensive framework that can revolutionize the way yoga is practiced, taught, and evaluated, ultimately promoting accessibility, precision, and effectiveness in the pursuit of physical and mental well-being.

Keywords— yoga pose, asanas, machine learning, deep learning, human pose detection, yoga pose recognition, CNN, LSTM, Media pipe, pose prediction.

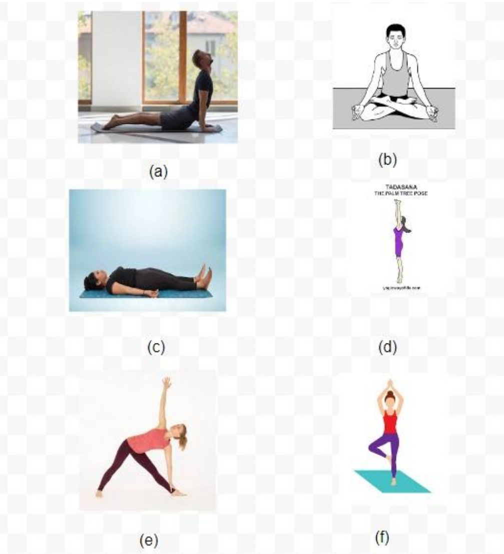
I. INTRODUCTION

Yoga, an ancient practice originating from India, has gained widespread popularity globally due to its numerous physical and mental health benefits. With its emphasis on mindful movement, controlled breathing, and meditation, yoga promotes holistic well-being. As technology continues to advance, there is a growing interest in integrating it with the practice of yoga to enhance its effectiveness, accessibility, and personalization. One area of research that has emerged in recent years is yoga pose detection, which involves developing automated systems to accurately identify and track yoga poses. Yoga pose detection holds significant promise in revolutionizing the way yoga is practiced, taught, and analysed. By leveraging computer vision and machine learning techniques, yoga pose detection systems can analyse images or videos of practitioners and provide real-time feedback on their pose alignment, posture, and movement. This technology offers several potential benefits, including enhanced self-correction, remote instruction, progress tracking, injury prevention, and personalized yoga programs.

This research paper's main goal is to design and create a thorough yoga pose identification system that accurately identifies and tracks yoga poses in real-time. Through an in-depth analysis of existing literature and methodologies using CNN and long short-term memory algorithms we aim to propose a novel framework that combines multiple modalities, such as RGB images, depth maps, and skeletal joint data, to achieve accurate and robust yoga pose detection. This study is significant because it has the ability to bridge the gap between technology and yoga practise. By providing practitioners with real-time feedback and guidance, yoga pose detection systems can facilitate proper alignment, reduce the risk of injuries, and enhance the overall effectiveness of yoga sessions. Moreover, the integration of remote instruction capabilities enables individuals to access expert guidance regardless of their geographical location, making yoga more accessible and inclusive.

In addition to the practical implications for practitioners, this research paper also contributes to the scientific understanding of yoga and its impact on physical and mental well-being. By analysing a wide range of empirical studies, we aim to explore the underlying mechanisms through which yoga positions have a positive impact on the mind-body system. This knowledge can further inform future research and pave the way for evidence-based yoga practices. The subsequent sections of this research paper will delve into the methodology, implementation details, and evaluation of the proposed yoga pose detection system. We will discuss the challenges associated with pose variation, occlusion, and complex body movements within the yoga practice. Additionally, we will explore strategies for data augmentation, model optimization, and performance evaluation to ensure the accuracy, robustness, and practical viability of the system.

In summary, the purpose of this study report is to promote yoga practise by designing a comprehensive yoga pose detection system. By combining Convolutional neural network (CNN) techniques and Deep learning algorithms, we strive to provide practitioners with a technological tool that enhances their practice, facilitates remote instruction, and furthers our understanding of the physical and mental benefits of yoga.



Yoga poses: (a)Bhujangasana, (b)Padmasana, (c)Shavasana, (d)Tadasana, (e)Trikonasana, (f)Vrikshasana

II. LITERATURE SURVEY

Human pose estimate research now includes an important area of study called yoga pose identification. Prior to the development of Deep Neural Network architecture and posture estimation frameworks, efforts had been made to develop automated and semi-automatic systems to evaluate physical activity and sports.[16] Open pose is used to record the user and identify key points, CNN is used to identify patterns between key points in a single frame, and LSTM is used to memorise the pattern (Santosh Kumar Yadav: 2019).

Deep neural networks have revolutionized human pose estimation from the traditional systems. Deep Neural network architectures are used to develop various pose estimation models which improves performance and reduces cost of human pose estimation. Open Pose, a popular open-source posture estimation model, was put forth in (Cao et al.; 2017). (Santosh Kumar Yadav; 2019) identified 15 key points from the yoga stance using the Open Pose model, and the recovered key points were then sent to a hybrid model of CNN and LSTM classifier for prediction. The angles of the pose are determined using the reference key points, and the inaccuracy is then calculated.

[12] (Jothika Sunney:2022) uses Media pipe Blaze pose model outperforms existing pose estimation frameworks forreal-time Yoga/Fitness applications. On a 20-core desktop CPU, Blaze Pose performs 25–75 times faster than Open Pose. Furthermore, Media pipe models produce key points in the x, y and z dimensions. Here z corresponds to the distance of the user from the camera. Thus, Media pipe provides 3D feature extraction without requiring depth sensors. There has not been much research combining Media pipe and Machine learning algorithms. A novel approach is proposed in this study by combining [12] Media pipe Blaze pose model with [12] XgBoost classifier for real-time yoga pose detection. The study also assesses how well deep learning and machine learning models perform on 3D Landmark data produced by Blaze pose model. The drawback of this model is that it cannot be used for multi-person detections.

In the absence of enough publicly available datasets for yoga pose detection, research could have focused on creating a new dataset with more poses. As well, rather than passing key points directly to the model, this work can be improved by considering the angle between key points. Also, providing additional feedback on how to correct a yoga pose in real-time could improve real-time feedback. Currently, the Blaze pose model identifies only one person in an image frame. Further research should be conducted to detect multiple people.

The use of convolutional neural networks (CNNs) and long short-term memory (LSTM) networks in combination to monitor yoga positions is explored in the study [7] (Debabrata Swain:2022). A database of six yoga positions practised by 15 participants was used in the study. While LSTM was used to record the temporal dependence of poses across time, CNN was utilised to extract features from the input photos. employed 45 photo frames to track yoga poses and a confusion matrix to determine recall, precision, and sensitivity. Using the media pipe library, the study first pinpointed important locations, then captured the coordinates in JSON format. The likelihood of each yoga stance for the current image sequence was calculated using the SoftMax level, and the pose with the highest probability was output.

The model achieved high accuracy with a training accuracy of 99.49% and a testing accuracy of 99.70%. The study shows that the proposed model shows promise for real-time monitoring of yoga practices. Overall, the research shows that there is potential for further improvements in sentiment analysis through the use of larger data sets, additional numerical features, combinatorial methods, and advanced machine learning techniques such as deep and transfer learning.

A deep learning model is suggested in the publication [10] (Upadhyay, A:2023) for tracking yoga postures. The model, which is based on Y_PN_MSSD, was designed to assist yoga practitioners in maintaining good form and preventing harm. Seven yoga poses from an open-source dataset are used in the study. In each frame, the model combines the Mobile Net SSD layer for person detection with the Pose Net layer for feature point detection The study [18] (DMohanetal:2022) suggests estimating yoga postures using various deep learning architectures. The study focuses on five often used poses: the tree posture, triangle pose, half-moon pose, mountain pose, and warrior pose. It uses photographs from S-VYASA Deemed to University. The suggested models make use of various deep learning architectures, such as Open Pose and Epipolar posture for the simultaneous identification of body, facial, and limb key points and 3D structure from 2D image human posture estimation, respectively. Media Pipe for colour picture and pinpoint, and Pose Net for video input. According to the study's findings, the Media Pipe design offers the highest estimation accuracy.

Furthermore, the accuracy of the Open Pose, Epipolar, and Pose Net approaches were compared in the study, with Open Pose having a 70% accuracy rating, Peripolar having a 50% accuracy rating, and Pose Net having an 80% accuracy rating. These results imply that pose estimation in a variety of applications, such as yoga posture monitoring, can benefit from the Media Pipe design.

The study suggests that further research is needed to expand the proposed technique for pose estimation and correction to include more advanced postures in yoga. The same methodology could be used with simple tools to improve the accuracy of pose estimation and correction, making it easier for individuals to practice yoga postures as a self-evaluation and biofeedback mechanism

[19] (Kumar D:2022). In this paper the methodology involves several steps. Firstly, the input images are pre-processed to eliminate noise and artifacts, although the specific techniques are not mentioned. Next, transfer learning is used to extract features from the pre-processed photos, utilizing the VGG16 model pretrained on the ImageNet dataset. To address the limited dataset of yoga postures, data augmentation techniques are employed, generating new images through transformations such as rotations, flips, and zooms.

A convolutional neural network (CNN) is then trained using the pre-processed and enhanced pictures for pose identification and categorization. The publication does not, however, go into much detail into the CNN's architecture. A SoftMax activation function and a cross-entropy loss function is used in the CNN's last layer. After training, the model is evaluated on a different collection of photos, albeit the details of the test set or the model's precision are not made explicit.

While the methodology appears reasonable, there are some potential flaws. The lack of information about the pre-processing techniques used is a limitation, as pre-processing plays a crucial role in image analysis. Additionally, the absence of details regarding the CNN architecture hinders a comprehensive understanding of the approach. Knowledge of the network design is important as it directly impacts the model's performance. Furthermore, the paper does not discuss the limitations or downsides of the proposed methodology, which is essential for a thorough evaluation of its strengths and weaknesses.

In conclusion, Deepak Kumar's paper offers a method for deep learning-based yoga posture recognition and classification. However, the paper's contribution to the field of yoga posture recognition and classification is diminished by the absence of information on pre-processing methods, CNN architecture, and a discussion of the approach's limitations.

The article "Real-time yoga posture recognition and correction system using Kinect sensor," published by [20] (N. A. Murthy:2022), introduces a system made to identify and correct yoga postures in real-time using a Kinect sensor. The system aims to provide immediate feedback and instruction to assist yoga practitioners in improving their postures. The paper discusses the significance of achieving perfect posture in yoga and highlights the limitations of conventional posture repair approaches. The authors provide a detailed explanation of the system's architecture and operation, supported by experimental data that validates its effectiveness.

The methodology employed in the study involves several key steps. The authors collected a dataset comprising 11 yoga postures performed by ten volunteers with varying ages and genders, capturing the poses using a Kinect sensor. Posture recognition is achieved by extracting features, such as joint locations, angles, and distances, from the recorded posture data utilizing the OpenNI and NITE libraries. Subsequently, an SVM classifier is trained to recognize the 11 yoga positions.

To correct the user's posture, the authors developed an algorithm based on the recognized and intended postures. The algorithm calculates the angles and distances between the user's joints and the correct posture, refining them iteratively. The system implementation is carried out using C# and the Microsoft Kinect SDK, enabling the system to capture the user's posture with the Kinect sensor, recognize the posture using the SVM classifier, and provide real-time feedback for posture rectification.

The accuracy of posture identification and posture correction are the two metrics the authors use to assess the effectiveness of the suggested system. We compare our results with a baseline system that merely recognises postures without providing input for correction. The experimental findings show that the proposed system outperforms the baseline system in terms of accurate posture correction and posture identification.

Upon reviewing the paper, no significant flaws or concerns were identified in the described methodology. However, as with any scientific study, there are potential limitations and areas for improvement. One limitation is the relatively small sample size of subjects used in the dataset collection, which may impact the generalizability of the results. Additionally, the reliance on the Kinect sensor for posture assessment and correction could be a potential drawback, as it may not be universally available or affordable for all users. Nevertheless, the authors acknowledge these limitations and discuss potential avenues for future research. Overall, the research presents a comprehensive approach supported by experimental data, contributing to the field of real-time yoga posture recognition and correction.

[21] The author gathered a dataset of pictures of yoga poses from many websites, including Google Images and individual pictures. There were 11 yoga poses in the dataset, and there were 60 photos for each pose. The photos underwent data pre-processing by being resized to 224 x 224 pixels and being made grayscale. Additionally, the photos were enhanced using methods like random rotation and horizontal flipping to expand the dataset. The YogaPoseNet architecture that has been presented consists of two completely linked layers after the first four convolutional layers. Eleven nodes, each of which represented a yoga position class, made up the output layer.

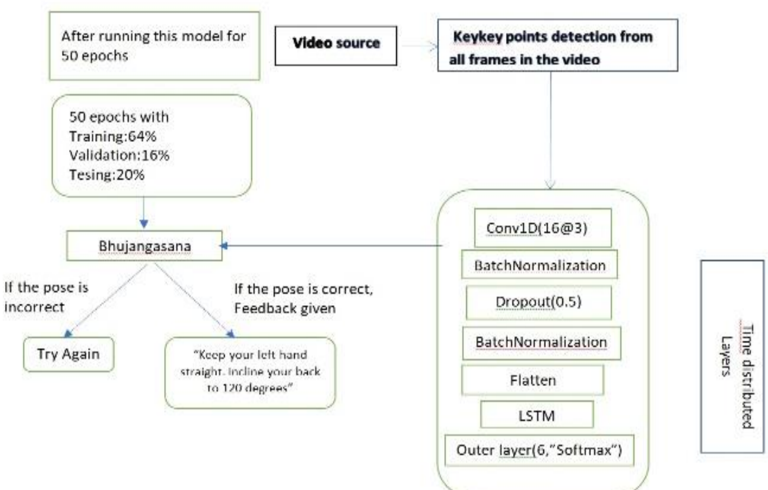
The authors used Rectified Linear Unit activation functions and dropout regularisation to improve the network's performance. The authors trained the model using the Adam optimizer and a categorical cross-entropy loss function. The dataset was split into a training set (80%) and a validation set (20%) for the purposes of training and validating the model. The scientists also employed early stopping and model check points to avoid overfitting and to maintain the best-performing model. The accuracy, precision, recall, and F1 score were only a few of the metrics the authors used to evaluate the YogaPoseNet model's performance. They also assessed the suggested model's performance in comparison to other deep learning models.

[22] This paper highlights the significance of stance detection and recognition in yoga. Although there have been earlier attempts to identify yoga postures, the accuracy of these techniques has been constrained, according to the authors. They mention how other applications have showed promise for the use of CNNs for stance detection and speculate that it would work well for yoga pose recognition as well. As part of the methods outlined in the research, yoga positions are taught to a CNN. The scientists used data augmentation techniques to gather a collection of 10,000 images that represented 15 different yoga stances in order to increase the dataset's size. Then, training, testing, and validation sets were created from the dataset. Three convolutional layers, each followed by a max pooling layer and two fully connected layers, were used by the authors to train a CNN. They employed the SoftMax activation function for the output layer and the Rectified Linear Unit (ReLU) activation function (BhattacharyaS:2022). The categorical cross-entropy loss function and the Adam optimizer were used to train the CNN. Early halting was employed by the authors to avoid overfitting. The accuracy for the 15-class classification issue, as reported by the authors, was 91.7% after they evaluated the model's performance on the testing set.

III. METHODOLOGY

An input for the suggested system is a real-time video series. Yoga posture predictions combined with advice on optimal angle and posture correction will be the outcome. Key point extraction, position prediction, and pose correction are the system's three core processes. Based on the user's position, the key point extraction phase seeks to identify and extract the locations of key points [14]. The phase of pose prediction categorizes whether or not the pose is valid and establishes the model architecture. stance correction is the last stage, during which the user is provided further feedback for correcting the stance and is shown the similarity percentage to the actual pose.

The suggested system architecture and the three aforementioned phases are shown in Figure 1.



A. Key points Extraction

In the first stage, all of the video's frames are used to extract keyframes, which are then stored in JSON format. Examples of key points include shoulders, elbows, wrists, knees, and other body parts that are important for the creation of a yoga position. For the purpose of extracting key points, we used the cross-platform Media Pipe library. produced by Google that offers incredible pre-built machine learning (ML) solutions for computer vision challenges. In body posture estimation, the image is used to estimate the body configuration (pos). The following primary steps make up the condition evaluation process:

1) Identification of the major joints and points on the human body.
2) Classify these projected joints.

We can calculate the distance between key points (e.g., shoulder to elbow, elbow to wrist) using the Euclidean distance formula to measure the length of different body segments:
Euclidean Distance:
For two points A(x1, y1) and B(x2, y2):
Distance = √((x2 - x1)^2 + (y2 - y1)^2)

The different joints of the human body initially establish the essential points. It comprises all general positions such as the eye, ear, neck, and shoulder. In the second stage, by grouping all of these joints, the entire structure of the body should be organized, and these primary points of grouping should forecast the person's position at any given time.

B. Pose Prediction

1)Model

Creating a deep learning model is the second stage. The objective is to accurately assign each of the videos to one of the six states listed in the dataset in real time. Here, CNN and LSTM are combined to create a deep learning model (Figure 2). LSTM is frequently used for time series issues and CNN is frequently used for pattern recognition issues. In our study, features are extracted from the 2D coordinates of the key points obtained in the previous stage using a temporal distribution layer to CNN. The SoftMax layer provides the likelihood of each run in the frame, and the LSTM layer analyses the variance of these features in the frame.

This work uses the Time Distributed layer combination with CNN, which is particularly usefulwhen working with video images or time series data [30]. In addition, a SoftMax level is used, which uses a fixed exponential function of to determine the probability of each yoga pose. As a result, the pose with the highest probability of is predicted.

2)Training

Media Pipe is used to extract key points, and the joint position values are saved in a JSON file. The CNN and LSTM models are then utilized to forecast asanas. Combining results in the best mix of filtered CNN features and long-term reliability of LSTM data.

C. Pose Correction

Following the classification of the projected posture as correct with respect to the specified pose, the user is given suitable feedback, and the similarity percentage (using cosine similarity) is calculated and reported to the user.

Cosine similarity is used to calculate the similarity between two vectors (e.g., the vector representing the user's pose and the vector representing the standard pose). It can be used to determine how closely the user's pose matches the correct pose:
Cosine Similarity:
Cosine(Θ) = (A · B) / (||A|| * ||B||)
Where A and B are the vectors representing two poses, · denotes the dot product, and ||A|| and ||B|| are the magnitudes of the vectors.

Important and significant angles have been determined and rules have been developed for each of the six yoga positions included in the dataset, which will be discussed more below. A threshold is established for each rule, which represents the user's maximum deviation from the conventional stance.

To establish the threshold for acceptable pose deviation, you can use a mathematical formula based on your specific requirements:

Threshold = a * (Standard Deviation of Key Point Distances)

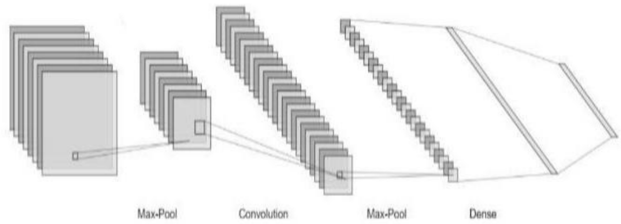
'a' is a scaling factor to control the threshold level.

If the user reaches this threshold value, he or she receives feedback in the form of text and speech. Calculating the tangent inverse of the slope with positive X-axis yields the angle between two key points. Equation below gives the formula for calculating the angle between two key point coordinates:

Angle (Θ) between two points (x1, y1) and (x2, y2):
Θ = arctan((y2 - y1) / (x2 - x1))

The communication is initially received as text, which is then turned into speech using the Pyttsx3 package [41]; this is a text to speech converter that also works offline.

The cosine similarity between the key points of the user's position and the standard position is determined in this work. As a result, this measurement represents the degree of similarity to the actual pose.



Convolutional Neural Network

IV. EMPERICAL ANALYSIS AND RESULT

There are three key steps in this section. For the movies captured by the webcam in the first stage, frame-by-frame results utilizing the CNN model and -LSTM are displayed. The results of the second phase, 45, are predicted from recorded videos after images have been analyzed. Results for recorded videos are given following a query of 45 photos. Higher and more consistent findings are attained when 45 frames have been surveyed. Actual prediction outcomes are shown in the third stage.

This model can predict six user posture sequences in a real-time setting and can validate the accuracy of the poses. The following factors are used to evaluate a yoga classification system:

A)Classification Score: The classification score typically represents the model's accuracy. It can be characterized as the proportion of accurate predictions to all input samples.

Classification Score = (Number of Correct Predictions) / (Total Number of Input Samples)

B) Confusion matrix: The correctness of the model is fully described by the confusion matrix. The confusion matrix can be used to determine metrics like as precision, recall, and precision score. and compute precision and recall using this data. Therefore, to score Fl, employ accuracy and recollection. It will be simpler to demonstrate how to calculate these things as a result. True negatives, true positives, false negatives, and false positives can all be counted. We always want the diagonal of the matrix to have the highest number of samples since the diagonal values indicate correctly identified data.

Precision = (True Positives) / (True Positives + False Positives)
Recall = (True Positives) / (True Positives + False Negatives)
F1-Score = 2 * (Precision * Recall) / (Precision + Recall)

C) Model accuracy and model loss curve: These curves, which are also known as learning curves, are typically employed for technologies like neural networks that analyze data incrementally over time. They make up the evaluation of the educational and validation data, which helps us determine how well the version is learning and generalizing. The model loss curve depicts a minimizing score (loss), meaning that a lower score results in better model performance overall. A higher grade indicates that the version performed better. A great fitting version loss curve has a small gap between the very final loss values and education and validation losses that decrease and reach a stable factor. The fitted model accuracy curve is a curve, though.

V. CONCLUSION

The evaluation of the human condition has received a lot of attention lately. In contrast to other computer vision problems, human pose estimation requires that body pieces be constructed and placed according to a predetermined human body form. Assessing your posture while exercising can help you avoid injuries and perform better. We contend that a self-study yoga programme may both popularize and guarantee proper yoga practice. Deep learning techniques have potential as a result of substantial research in the area.

An efficient real-time yoga monitoring system was presented in this paper. The Media Pipe library is used to first locate user-specific key points, then key coordinates are then captured and saved in JSON format. Then, we transmit a 45-image sequence that was created in real time to the model. The model in the example below uses CNN and LSTM in conjunction to identify useful characteristics and track the appearance of image sequences. The SoftMax level at the conclusion of calculates each yoga pose's probability for the current image sequence and outputs the pose with the highest probability of. More specifically, the user is given the output, which is 45 frames for each frame in counting mode.

If the pose is deemed accurate, the user receives additional feedback based on a predetermined threshold. The threshold, in particular, is established to guarantee that the user maintains exact locations and angles while not overtaxing the machine. Finally, the user is shown a similar percentage of when compared to the default stance.

VI. FUTURE WORK

Only six yoga asanas are currently classified using the proposed models. There are many different yoga asanas, hence it is challenging to develop a posture assessment model that works for all asanas. By including more yoga positions done by people both indoors and outside, the dataset can be increased. The accuracy of the Open Pose pose estimation, which may not be effective when persons or body parts overlap, determines how well the models perform. This system can be implemented as a portable gadget that self-learns and makes predictions in real time. Performance detection for real-world applications is shown in this paper. Position can be determined using a similar method in tasks like sports, surveillance, healthcare, etc.

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