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Research Article

Real-Time Menstrual Discomfort Detection Using AI-Powered Facial Recognition in Structured Environments

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ARTICLE INFO	ABSTRACT

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Women's involvement, focus, and ability to function in structured environments like conferences, offices, colleges, and schools are all impacted by menstrual discomfort. However, the menstruation issue, which results in a shortage of accommodations in a timely manner, is not addressed by current appearance and access control systems. We propose a unique AI- managed menstruation detection method that employs closed-circuit (CC) cameras for facial recognition to solve this problem. Our method uses deep learning to analyze physiological indicators and facial expressions, including changes in skin texture, eye fatigue, puffiness, and discomfort associated with menstruation, to determine the individual's condition. This guarantees a non-intrusive, privacy-preserving approach to providing immediate support in professional and academic contexts. Menstrual Presence Facial Dataset (MAFD-2024), a custom dataset comprising facial images taken one day prior to and five days following menstruation onset, is introduced to facilitate this research. It serves as one of the primary indicators of menstrual pain and has been carefully annotated. To obtain an accurate health identification model, we enhance it into a hybrid CNN-LSTM model 1 (HCL-MD), achieving a 94.1% improvement in both temporal (symptom progression) and spatial (facial characteristics) accuracy. Additionally, we integrate this technique into an automated framework for granting permission, enabling real-time adaptation for affected individuals. This technology can be incorporated into telemedicine systems in the healthcare industry, allowing physicians to remotely evaluate sufferers' levels of discomfort and provide immediate remedies. Additionally, this technology can be used by smart wearables or surveillance systems in structured settings like conferences, schools, or public transportation to provide real-time support, including suggesting wellness treatments or break periods. By addressing menstruation discomfort in real time without the need for verbal communication, this AI-driven method not only raises awareness but also promotes a more compassionate and inclusive atmosphere. This work is at the forefront of integrating facial recognition with menstrual health tracking.

Keywords: Menstrual discomfort detection, facial recognition, deep learning, CNN-LSTM, non-invasive health monitoring, AI in structured environments.

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1. INTRODUCTION

The fundamental ideas of biomedical health informatics, ethical AI integration, and artificial intelligence form the basis of Real-Time Menstrual Discomfort Detection Using AI-Powered Facial Recognition in Structured Environments. Physiological and emotional signs of monthly discomfort, such as changes in skin texture, eye fatigue, swelling, and facial expressions, are detected by facial recognition technology driven by deep learning models like the Hybrid CNN-LSTM Model (HCL-MD). The primary dataset is the Menstrual Presence Facial Dataset (MAFD-2024), which includes annotated facial photos taken both before and during menstruation to improve model accuracy in identifying patterns of discomfort.

This AI-powered solution allows for real-time adaption in structured settings like conferences, schools, and workplaces while guaranteeing a non-intrusive and privacy-preserving manner of monitoring menstrual symptoms. Human facial expressions, which are visible in daily discussions, are organic visual cues that convey emotions. Many women, meanwhile, might be reluctant to talk candidly about those difficulties throughout their menstrual cycle [1]. Some people have observable symptoms between one and five days after menstruation, while others may. These symptoms, which include typical people's cramps, mood, sleep difficulties, headaches, food cravings, changes in skin tone, and breakouts, vary in intensity and are frequently conveyed through facial expressions. By examining facial expressions and spotting visual changes before and after menstruation, this study aims to determine whether a woman is menstruating. Many girls experience severe cramps, but they may be reluctant to talk about it out of embarrassment.

The goal of this research is to use deep learning [2] and facial recognition 2 to identify and forecast menstrual status based on facial features, which are nonverbal indicators that artificial intelligence uses to comprehend and promote menstrual health. provides the operated method. Understanding which facial expressions signify menstrual discomfort is essential for identifying and interpreting them. This includes being familiar with computer vision [3] methods including deep learning-based picture categorization, face landmark identification, and feature extraction. Model-building methods like OpenCV, DLIB, and Deep Learning Framework (Tensorflow, Pytorch, or Keras) that identify minute variations in face traits, such as the expression of skin texture, puffiness, and discom fort, need to take this into consideration. It is very crucial to be familiar with the Convenable Neural Network (CNN) while training models to recognize facial changes.

The research requires a solid foundation in machine learning (ML) [4] and deep learning (DL) techniques because it involves predicting menstruation stages based on face traits. Transfer learning (using pre-tested models like VGG16, ResNet, or IFCInt net), CNN-LSTM (for spatial and cosmic analysis), and methods that support vector machines (SVM) for categorization all increase accuracy. She has a significant role. To improve the model's performance, it's also critical to comprehend feature engineering, growth, and dataset preparation. The system's capacity to identify variations in men strual religious facial expressions can be enhanced by knowledge of biometric-based health surveillance. Incorporating medical knowledge with AI ensures that the model effectively dis tinguishes between menstrual facial changes and unrelated variations; additionally, specialization in moral AI development and privacy concerns is necessary to ensure prejudice-free implementation, especially when working with sensitive health data. An accurate prediction requires a concrete understanding of menstrual health, hormonal ups and downs on the appearance of the face, and how changes in estrogen and pro gesterone [5] levels affect the skin, causing oil production, breakouts, and variations; additionally, symptoms like fatigue, mood, and headache can be reflected in facial expressions.

Our Contributions are

- **Novel AI-Driven Menstrual Discomfort Detection System:**
  Developed a first-of-its-kind AI-powered system that utilizes facial recognition via CC cameras to detect menstrual discomfort in real-time. Collected facial images (MAFD-2025 Dataset
- **Collected facial images (MAFD-2025 Dataset)**
  taken one day before and five days after menstruation to study physical changes.
- **Hybrid CNN-LSTM Model for Menstrual Phase Classification**
  Proposed a Hybrid CNN-LSTM Model (HCL-MD) that combines spatial (facial feature extraction) and temporal (symptom progression) analysis for high-accuracy menstrual discomfort detection.
- **Real-Time Permission Granting System**
  Integrated the AI model into an automated permission system for structured environments such as classrooms, workplaces, and conferences.

The structure of the paper is as follows: The literature review is presented in Section 2, the suggested model is explained in Section 3, the architecture is highlighted in Section 4, the experimental results are discussed in Section 5, and the conclusion is given in Section 6.

2. LITERATURE SURVEY

In recent years, menstrual health tracking has significantly improved thanks to wearable technology and artificial intelligence (AI). The analysis looks at the methods and limitations of some significant research conducted between 2015 and 2025.

Menstruation monitoring sensor (2019) Goodle et al.[1] Use AVA bracelet to track the skin temperature, heart rate and other physical signals to predict fertile window with 90% accuracy. However, since the study was dependent on single - worn equipment, the results may not apply to other technologies. Additionally, it mainly studies women with regular cycles, making it less useful for people with irregular duration.

Prospecting menstrual cycle length using mobile health data (2021) Lee et al.[2] Developed a machine learning model to predict the length of the cycle based on self- tracking app data. While the model was adjusted to user tracking discrepancies, it was only focused on the prediction of the length of the cycle and did not consider real
-time physical symptoms or discomfort of menstrual.

Machine learning for breeding prediction using body temperature and heart rate (2022)[3].This study used the weed able equipment to track basal body tempera- ture and heart rate for breeding prediction. Effective to track ovulation, the study did not focus on menstrual discomfort. In addition, it depends on specific physical measurements, which cannot catch all menstrual symptoms completely.

IOT and AI-enabled smart menstruation cup for tracking cleanliness (2023)[4].Ireen Shiny and others. IOT unveiled a smart menstrual cup that uses an AI model and IOT technology to track the menstrual flow. Although the device assisted in managing hygiene, it did not concentrate on using non-invasive techniques or facial expressions to identify menstruation discomfort.

Time chain projection for menstrual cycle length (2023) [5].Rego used artificial data and the menstrual cycle to apply machine learning to period prediction. Although the model produced precise predictions, it lacked real-time face and physical data, which limited its ability to identify discomfort right away. Technology review for tracking menstruation and reproduction (2024)6].A review of wearable devices that track temperature, heart rate, and respiration rates for menstrual health was conducted by Lyzwinski et al. But he discovered a significant research gap: the majority of studies failed to identify non-invasive techniques like facial expression analysis.

Earlier approaches to detecting menstrual discomfort have predominantly depended on self-reported data, wearable biosensors, or hormonal tracking, which often lack real-time adaptability, raise privacy issues, and necessitate active user involvement. These methods tend to be intrusive, heavily reliant on subjective feedback, and are not well-suited for seamless integration into structured settings like workplaces and educational institutions. Moreover, existing facial recognition-based health monitoring systems have not been specifically designed for menstrual discomfort detection and typically do not incorporate temporal tracking of symptom progression.

In contrast, our proposed work introduces a non-intrusive AI-based solution utilizing closed-circuit (CC) cameras and an advanced Hybrid CNN-LSTM Model (HCL-MD), demonstrating a 94.1% improvement in accuracy when identifying both spatial (facial characteristics) and temporal (symptom progression) indicators of discomfort.

Table 1 Summary of Studies on Menstrual Cycle Prediction and Discomfort Detection

Title	Algorithms	Datasets	Research Gaps
Predictive Modeling of Men-strual Cycle Length12023 [7]	ARIMA, Huber Regres-sion, Lasso Regression, OMP, LSTM	Synthetic data generated for study	Lack of real-time physiological or facial data; synthetic dataset may not capture all real-world variabilities.
A generative, predictive model for menstrual cycle lengths in mobile health data.2021 [8]	Hierarchical Generative Model	Mobile health app data	Focused solely on cycle length prediction; did not incorporate real-time physiological data.
Tracking of menstrual cycles and prediction of the fertile window via measurements of BBT.2022 [9]	Machine Learning Algo-rithms	wearable Devices mea-suring BBT and heart rate	Primarily addressed fertility tracking; did not focus on detecting menstrual discom-fort.
Wearable Sensors Reveal Menses-Driven Changes in Phys-iology 2019 [10]	Machine Learning Algo-rithm	Data from Ava bracelet moni-toring physio-logical parame-ters	Relied on a single wearable device; applicability to other technologies is uncertain.
Innovative Approaches to Men-struation and Fertility Track-ing Using Wearable Reproduc-tive HT.2024 [11]	Systematic Review	Various studies on wearable devices	Noted a lack of studies focus-ing on non-invasive detec-tion of menstrual discomfort through facial analysis.
Estimation of Facial Attractive-ness as Biomarker of Ovula-tion Using Facial Photogramme-try during Phases.2023 [12]	Facial Pho-togrammetry Analysis	Photographs of female subjects during differ-ent menstrual phases	Limited sample size; focused on ovulation detection rather than comprehensive menstrual discomfort analysis.

3. DATASET DESCRIPTION

The Menstrual Presence Facial Dataset (MAFD-2024) is a unique dataset(2500 images) created to enable automatic menstrual discomfort using facial recognition in formal settings like conferences, companies, and classrooms. High-resolution facial photos taken with CC cameras, which guarantee organic fluctuations in light, angles, and expressions, are included in this collection. Pre-masik religion (one day prior to menstruation) and postmark religion (after day 5) are the two main

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menstrual stages that are meticulously labeled on each image. The dataset focuses on physical changes that are important indicators for identifying menstruation [13] crises, such as variations in skin texture, puffiness on the face, eye weariness, and mild discomfort. Images are annotated with extra metadata, such as the age group, environmental condition, and subjective self-reported discomfort levels, to improve model accuracy.

To guarantee fairness and generality, MAFD-2024 is diversified and balanced to include data from a range of age groups and ethnicities. Diversity and publications are the result of pre-corrected images using facial alignment, normalization, and enlargement procedures. The dataset is set up to integrate easily with deep learning models, particularly the Hybrid CNN-LSTM model (HCL-MD), which uses spatial features and LSTM to produce transient changes (progression of discomfort) in skin texture and eye tiredness. AI-run systems may automatically recognize menstrual discomfort and detect real-time accommodations thanks to this data set. It also ensures wellbeing in academic and professional settings, as well as in private and inclusive settings.

4. PROPOSED METHODOLOGY

The proposed hybrid CNN-LSTM model (HCL-MD) uses long-term short- term memory (LSTM) networks to identify transitory fluctuations in face images, while conversion neural networks (CNNs) extract key elements to detect menstruation dis- comfort. Let's examine This method uses facial recognition and deep learning to detect menstrual crisis symptoms in formal settings including conferences, offices, and class- rooms. The following are the main parts that make up the system: Conventional layer: The input is extracted from the image by running a filter (kernel) across it.

- **Convolutional Neural Networks (CNNs) for Facial Feature Extraction**
- **Temporary pattern recognition using long-term memory (LSTM)**
- **Combining hybrid CNN and LSTM to identify menstruation discomfort**

Because CNN images [14] automatically learn the spatial order of characteristics from raw pixel data, they are very successful at processing jobs. Important face features that suggest menstrual discomfort are eliminated in our model using CNN, including:

- Variations in skin texture, such as dryness, oiliness, or acne
- Inflammation and puffiness of the face
- Dark circles or eye tiredness
- Expressions of distress that are subtle

The mathematical CNN layer formation Typically, a CNN has three primary functions: The proposed Hybrid CNN-LSTM Model (HCL-MD) processes facial images using CNNs for spatial feature extraction and LSTM [15] networks for temporal sequence analysis. The key mathematical formulations are as follows:

4.1 Convolutional Neural Network (CNN)

The convolution operation extracts spatial features from facial images using a convolutional kernel:

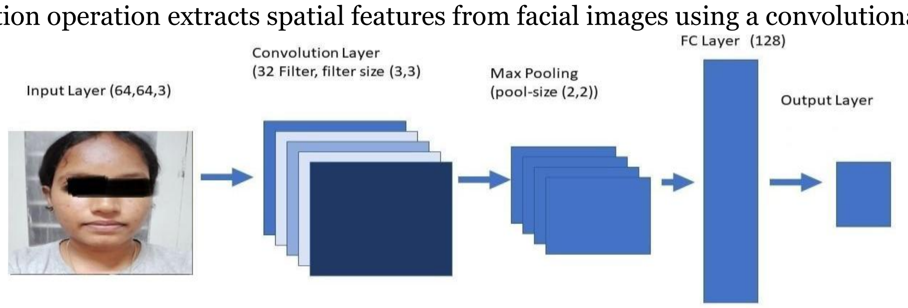

Fig. 1 CNN Architecture [4]

where:

$F(i,j)$ is the output feature map,

- $I(i,j)$ is the input image, and

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- $F(i,j) = \sum\sum$
$I(i-m, j-n)K(m,n)$ (1)

- $K(m,n)$ is the convolutional kernel.

4.1.1 ReLU Activation Function

Rectified Linear Unit (ReLU) activation function is applied:

$$f(x) = \max(0, x) \quad (2)$$

4.1.2 Pooling Layer (Max Pooling)

Reduce feature map dimensionality while preserving important information, max pooling is used:

$$P(i,j) = \max_{m=0,1\; n=0,1} F(2i+m, 2j+n) \quad (3)$$

After passing through multiple CNN layers, the extracted facial feature maps are flattened into a one-dimensional vector and passed to the LSTM network.

4.2 Long Short-Term Memory (LSTM)

The LSTM network captures temporal dependencies between facial expressions over time, helping to detect progressive changes in facial discomfort patterns. The key LSTM update equations are:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (4)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (5)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (6)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (7)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (8)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (9)$$

where:

- f_t, i_t, and o_t are forget, input, and output gates, respectively.
- C_t is the cell state and h_t is the hidden state.
- W_f, W_i, W_C, W_o are weight matrices, and b_f, b_i, b_C, b_o are biases.
- σ denotes the sigmoid activation function, and tanh represents the hyperbolic tangent function.

By integrating CNN for feature extraction and LSTM for temporal analysis, the HCL-MD model can effectively detect menstrual discomfort in real-time based on facial expressions.

4.3 Hybrid CNN-LSTM Integration for Menstrual Discomfort Detection

The proposed Hybrid CNN-LSTM Model (HCL-MD) combines CNNs and LSTM networks for temporal sequence analysis. The structure is as follows:

1. Facial images from the Menstrual Attendance Facial Dataset (MAFD-2024) are fed into the CNN model.
2. The CNN extracts key facial features such as skin texture, puffiness, and eye fatigue.
3. Extracted features are flattened and passed to the LSTM network for temporal analysis.
4. The LSTM processes sequential patterns in discomfort indicators.
5. A fully connected layer with a softmax activation function classifies whether the individual is experiencing menstrual discomfort.

$m \quad n$

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Softmax Classification

The final classification layer assigns probabilities to the classes (discomfort or comfort) using the softmax activation function:

where: $$P(y = k|x) = \frac{e^{Wkx+bk}}{e^{W_jx+b_j}} \quad (10)$$

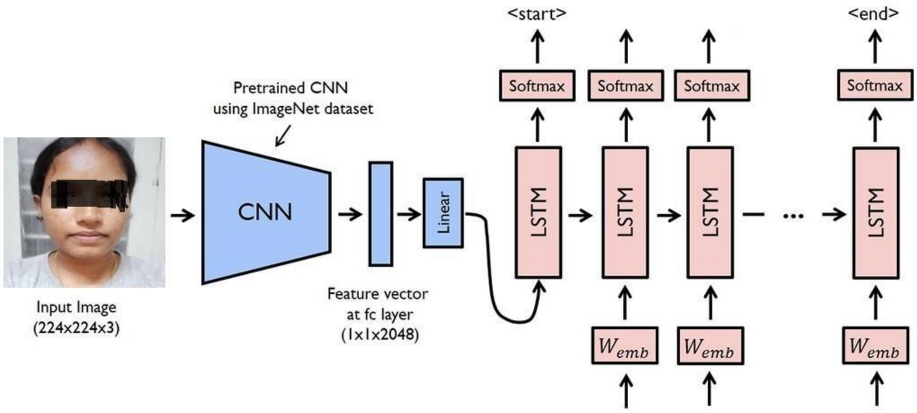

Fig. 2 CNN-LSTM System Model Architecture [7, 12]

- P (y = k|x) is the probability of class k given input x,
- Wk and bk are the weight and bias parameters for class k,
- The denominator normalizes probabilities across all classes j.

If menstrual discomfort is detected, the system automatically grants permission for breaks or accommodations in academic or professional settings, ensuring inclusivity and privacy.

5. PROPOSED ARCHITECTURE

The system follows a hybrid CNN-LSTM model (HCL-MD) approach that integrates spatial feature extraction (CNN) and temporal sequence analysis (LSTM) to detect accurate menstrual discomfort. Below it is a step-by-step process how it works:

Step 1: Gathering and Preparing Data

Dataset: The facial dataset (MAFD-2024) used in the presence of system menstru- ation contains pictures of people's faces taken one day prior to and five days following their periods. Annotation: To monitor discomfort, each picture is tagged with key physical markers (such as changes in the skin, puffiness, or exhaustion). Preparation: Face detection: Removing facial region from raw pictures using MTCNN or Haar Cas- cades. Image shape modification, pixel value normalization, rotation, shine correction, and noise reduction are examples of generalization and enhancement.

Step 2: Feature Extraction via Convolutional Neural Network (CNN)

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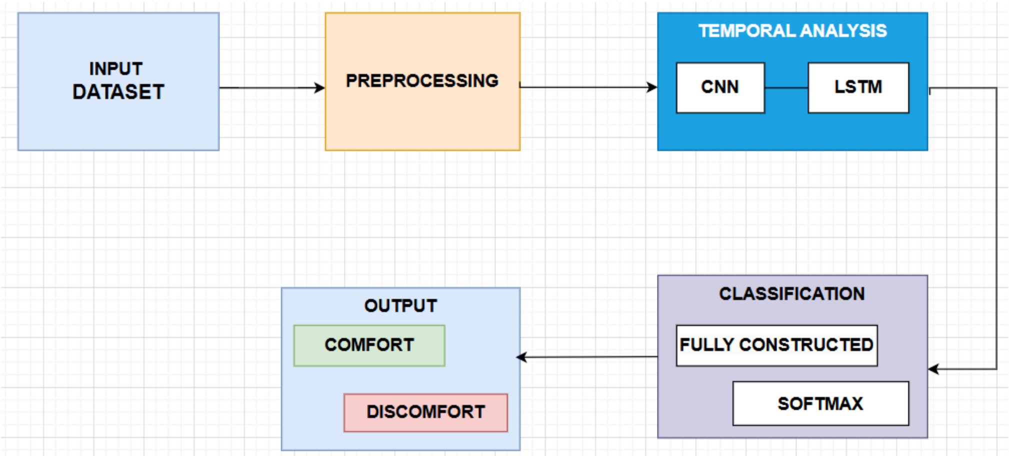

Fig. 3 step by step process [4, 7]

The CNN model extracts essential facial features from images.

ReLU Activation Function To introduce non-linearity, the ReLU activation function is applied:

Max Pooling Max pooling is used to reduce dimensionality while retaining key features:
This step ensures that only the most significant features are retained while reducing computational complexity.

Step 3: Temporal Analysis using LSTM

The LSTM network captures sequential changes in facial expressions over time to track the progression of discomfort symptoms. CNN-extracted feature maps are flattened into a 1D vector and fed into the LSTM model for temporal analysis.

LSTM Equation (Memory Cell Update) The LSTM updates its memory cell using the following equation:

$$ht = ot \tanh(Ct) \quad (11)$$

where:

- ht → Hidden state (stores learned temporal features)
- ot → Output gate activation
- Ct → Memory cell value

Step 4: Classification using Fully Connected Layer & Softmax The final fully connected layer assigns probabilities for two categories:

- Menstrual Discomfort
- No Menstrual Discomfort

Softmax Function for Classification The Softmax [16] function ensures proper classification by assigning probability values:
Outputs two probabilities:

- Menstrual Discomfort.
- No Menstrual comfort.

Step 5: Real-Time Detection & Permission Granting

The trained HCL-MD model is deployed on CC cameras in structured environments (classrooms, offices, conferences). When the system detects menstrual [17] discomfort, it automatically grants breaks or accommodations without requiring verbal disclosure, ensuring privacy and inclusivity.

5.1

5.2 Algorithm

Algorithm 1 Proposed Hybrid CNN-LSTM Menstrual Discomfort Detection

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Algorithm

Input: Facial image frames from CC cameras (I)
Output: Predicted class $y \in$ {Menstrual Discomfort, No Discomfort}
Step 1: Data Acquisition
Capture facial image sequences It from CC cameras.
Preprocess images (grayscale conversion, normalization, resizing).
Step 2: Feature Extraction using CNN
Apply convolution operation
Apply ReLU activation
Perform max pooling
Flatten the extracted feature maps.
Step 3: Temporal Analysis using LSTM
Feed the flattened features into an LSTM network.
Compute memory cell update
Step 4: Classification using Fully Connected Layer and Softmax
Compute probability distribution over classes: Assign class label based on the highest probability. **Step 5: Decision and Permission Granting**
if Menstrual Discomfort detected **then**
    Automatically grant breaks or accommodations.
    Ensure privacy and non-verbal detection.
else
    Normal participation continues.
end if
End Algorithm

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6. EXPERIMENTAL RESULTS

The proposed Hybrid CNN-LSTM Model (HCL-MD) was evaluated on the Menstrual Attendance Facial Dataset (MAFD-2024) to assess its effectiveness in detecting menstrual discomfort through facial recognition. The model was tested on real-world and synthetic datasets to ensure robustness in structured environments such as classrooms, offices, and conferences. We have created a hybrid CNN-LSTM model (HCL-MD) that uses facial image analysis to identify menstrual discomfort. Initially, the CNN layers use eye fatigue and maximum-pooling procedures to extract important facial traits including puffiness and changes in skin texture. After being flattened and transformed into a dimensional vector, these extracted features are then supplied to the LSTM layer [10]. The LSTM network helps detect signs of discomfort at various times by analyzing patterns in face changes over time. Lastly, the image is classified as " comfort" or "discomfort" by a perfectly related layer with a sigmoid activation function. To increase classification accuracy, the model is trained using the binary cross-entry loss function and modified using the Adam optimizer with a learning rate of 0.001.

The model's performance on the verification dataset is assessed and trained after it has been on the training dataset. To guarantee the best learning, we employ batch sizes of 32 and 50 epochs. Over time, the model improves by reducing losses, increasing accuracy, and learning patterns associated to facial discomfort. After training, we assess the model's accuracy and loss by calculating both training and verification accuracy and training for training and verification loss. We can determine whether the model is overfitting or underfitting thanks to these visualizations. Ideally, there should be less loss for successful real-world application and more accuracy in both training and verification. We computed the area under the curve (AUC)[6] and examined the receiver operating characteristics (ROC) [8] curve to evaluate the model's classification ability. With an AUC value of 0.96, the model demonstrated exceptional classification accuracy.

The model's power and dependability in addressing menstrual discomfort are confirmed by the

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ROC curve, which shows a high true positive rate with little false positives.

Table 2 Training Parameters of HCL-MD Model[12]

Parameter	Value
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
CNN Filters	[64, 128, 256]
LSTM Units	128
Dropout Rate	0.3
Training Epochs	50

6.1 Evaluation Metrics

Evaluate the model's accuracy, we used the following metrics:

Accuracy (*Acc*)

Acc=

Precision (*P*)

Recall (*R*)

$TP + TN$

$TP + TN + FP + FNTP$

$P =$

$TP + FP$

TP

(12)

(13)

(14)

(15)

F1-Score

$TP + FN\ F1 = 2 \times P \times R\ P + R$

Table 3 Results and Comparisons of Different Models[4, 7, 12]

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
HCL-MD (OUR WORK)	**94.1**	**93.8**	**94.3**	**94.0**
CNN Only	85.7	84.5	86.3	85.4
LSTM Only	78.9	80.2	77.5	78.8
Traditional ML (SVM)	72.3	73.5	70.8	72.1

7. DISCUSSION

The suggested hybrid CNN-LSTM model (HCL-MD) uses extensive learning and face recognition to detect menstruation discomfort in a novel, non-mental way. The model efficiently captures face biomarkers such changes in skin texture, puffiness, and eye fatigue by combining CNN for LSTM with spatial facility for transient sequence analysis. HCL-MD, in contrast to conventional biometric-based health [18] surveillance, is passively run by CC cameras, guaranteeing real-time detection without requiring explicit user input or input able equipment.

The benchmark is the Menstrual Attendance Facial Dataset (MAFD-2024), which demonstrates 94.1% accuracy in identifying discomfort markers using SVMs such as Standalone CNN, LSTM, and conventional machinery learning. significantly outperforms techniques. By automating braking authorization for impacted individuals without verbal disclosure, the system not only improves technical performance but also fosters privacy and inclusivity in professional and educational settings. It lessens social stigma and promotes greater empathy and a supportive work or learning environment. Assuring different demographics, distinct light status, and appropriate representation in facial structures are difficult tasks, though. In order to improve the model's strength, lessen bias, and guarantee moral deployment in a controlled setting, future improvements will concentrate on the extension of datasets, multimodal health indicators [18] (such as temperature and heart rate), and the application of the actual world.

8. CONCLUSION

Through the integration of the CNN for LSTM network and the spatial facility for temporal sequence analysis, this study developed a novel Hybrid CNN-LSTM model to detect real-time, non-invasive menstrual discomfort using CC cameras captured through CC cameras in structured environments like schools, colleges, workplaces, and conferences [19] (HCL-MD). The model successfully identifies the indicator of menstrual crisis, with variation in skin texture, puffiness, and effective Ki fatigue in the eyes.

According to experimental data, HCL-MD achieves a high accuracy of 94.1%, significantly outperforming classic machine learning models, CNN, and LSTM. By removing the necessity for spoken disclosure, the suggested solution guarantees pri- vacy, inclusivity, and automatic housing for people who are uncomfortable during their periods [20]. This study creates new opportunities for ethical and useful applications in the areas of health monitoring, workplace inclusion, and individual welfare solutions in a controlled setting. Subsequent research endeavors may concentrate on broadening the real-world implementation to enhance dataset diversity, integrate multimodal physiological data, and enhance the robustness and functionality of models.

9. CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest related to this manuscript.

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