V.Sujatha, 2026, 14:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science,
Engineering and Technology
An Open Access Journal

Based On Quantum Cryptography, Blockchain, And Dcnn To Determine Emotions From Facial Expressions

V. Sujatha[1], B. Sri Sai Kavya Samhitha[2], B. Vyshnavi[3], M. Mallika[4], P. Teja[5]

Department of CSE, Vignan's Nirula Institute of Technology and Science for women
Palakaluru, Guntur, 522009, Andhra Pradesh, India.
s

Abstract: Facial expression-based emotion recognition plays a crucial role in sectors such as healthcare, security, education, and human-computer interaction, yet achieving accuracy, privacy, and security remains challenging. This research proposes a secure and reliable emotion recognition framework by integrating Deep Convolutional Neural Networks (DCNN), blockchain technology, and Quantum Cryptographic Distribution (QCD). The framework employs a DCNN trained on diverse datasets to ensure resilience against variations in lighting, occlusion, and facial diversity. It captures facial images or video frames, extracts spatial and texture-based features, and utilizes these features for emotion classification. QCD provides post-quantum cryptographic security for data transmission, while anonymized results, timestamps, and hashed feature vectors are securely stored on a permissioned blockchain. Experimental evaluation on benchmark datasets (FER2013, CK+, and JAFFE) demonstrates superior performance compared to traditional CNN, VGG16, and ResNet50 models, achieving 97.8% accuracy, high precision (~0.98), recall (~0.98), and F1-score (0.98). The system is suitable for privacy-sensitive applications as it ensures tamper-proof, auditable, and real-time emotion recognition. By combining blockchain immutability, quantum-secured communication, and AI-driven classification, the proposed framework offers a secure, interpretable, and future-proof solution for emotion recognition in practical applications.

Keywords: Deep Convolutional Neural Networks (DCNN), Blockchain, Quantum Cryptography, Data Security, Real-time Emotion Detection

I. INTRODUCTION:

Due to its numerous applications in domains like marketing, security, healthcare, and human-computer interaction [1] [2]. Facial expression-based emotion recognition has emerged as a crucial research topic [3]. Systems can react sympathetically[3]. And adaptively when human emotions are accurately deduced from facial cues [4]. Improving decision-making and user experience [5]. However, protecting the confidentiality, integrity, and security of the sensitive data involved is a major challenge for emotion recognition systems, particularly when working with live facial images and video streams [6] [7].

Even with improvements, current emotion recognition models frequently face a number of drawbacks [7] [8]. Numerous strategies mainly rely on centralized data storage, which presents issues with data breaches, illegal access, and emotional data manipulation [9]. Furthermore, environmental factors like lighting and occlusion, as well as the inherent variability in facial expressions among people, frequently lower the accuracy of recognition systems [10] [11]. Moreover, the scalability and real-time applicability of many existing models are restricted by the computational complexity and latency involved in processing high-dimensional facial data [12].

This study suggests a novel framework for reliable and secure emotion recognition from facial expressions by combining blockchain technology with Quantum-inspired Clustering and Detection (QCD) techniques [13]. The model uses the decentralized ledger of blockchain technology to guarantee transparent management and safe, tamper-proof storage of emotional data, while QCD improves the precision and effectiveness of emotion classification [14]. Improving emotion recognition systems' privacy and dependability, cutting down on processing latency, and facilitating scalable deployment in practical applications are the main goals of this research.

II. LITERATURE SURVEY

Abhilasha Sharma et al[1]. used the FER2013 and CK+ datasets to apply machine learning and deep learning models (CNN, VGG16, hybrid approaches) for real-time facial expression recognition [15]. Their hybrid models performed better than single models and produced scalable, accurate emotion prediction that is helpful in the fields of healthcare, education, and security [16]. They did, however, have to deal with privacy issues, limited emotion categories, dataset dependency, and high computational costs. Dong Seog Han et al[3]. suggested deep learning landmark models that integrate Mediapipe BlazeFace, MTCNN, and RetinaFace and incorporate attention mechanisms for emotion recognition [17]. Accuracy, scalability, and efficient feature extraction from actual data were guaranteed by the system. However, it had issues with real-time performance, needed a lot of processing power, and had trouble identifying subtle facial emotions [18] [19].

Carlos Busso et al. presented expert models and RNN-based mini-classifiers for analyzing emotional video frames. Their method outperformed conventional models in handling conflicting emotions, achieving 74.5% accuracy [20] [21]. However, using multiple expert models increased complexity, accuracy decreased with poor video quality, and balancing expert models ran the risk of bias.Vishal Singh Bhati et al.[6] created specialized deep learning architectures (EmoExtractNet + EmoRecogNet) using datasets like RAF-DB, CK+, KDEF, JAFFE, and FER2013, supported by Grad-CAM and t-SNE visualizations [22] [23]. They improved precision and adaptability in healthcare applications by using YOLOv8, Faster R-CNN, and MTCNN for detection [24]. However, overlapping emotions, low accuracy for small datasets, low robustness in comparison to fully supervised models, and high annotation demands were issues they had to deal with [25].

Win Shwe Sin Khine et al. [8] investigated CNN features and joint embedding space for emotion vector semantic embeddings (Word2Vec, GloVe) for zero-shot learning on FER2013 and CK+. Their model made it possible to recognize invisible emotions across domains in a scalable and affordable manner [26] [27]. However, sensitivity to word embeddings, extra processing overhead, and linguistic ambiguity limited accuracy on large datasets.Auh-yeon Dong et al. [10] employed remote photoplethysmography (rPPG), convolutional recurrent neural networks (CRNN), and multi-task learning (MTL) using the DEAP and MAHNOB-HCI datasets [28]. Using non-contact HR measurement, their approach increased the accuracy of emotion recognition by 6.85%. However, it had several drawbacks, including limited emotion categories, sensitivity to task weight, dataset dependency, and the incapacity to generalize HR estimation outside of controlled settings [29] [30].

William Eduardo Villegas-Ch et al. [12] used CNN-based neural networks for image processing and facial recognition in the classroom. Their system helped teachers monitor emotional patterns and modify their teaching methods by giving them real-time feedback on students' emotions [31] [32]. However, it was impacted by bad camera angles, needed balanced datasets, struggled with conflicting emotions, and lacked contextual understanding [33]. Manish Rathod et al. [14] used DL models (LSTM, CNN, RNN) and machine learning (ML) models (Random Forest, SVM) with the extraction of geometric and appearance features [34] [35]. Their framework supported HCI, security, and mental health by enabling silent, real-time emotion communication [36]. However, performance differed by age, culture, and person, posed privacy and ethical issues, had trouble detecting micro-expressions, and needed big datasets with a lot of processing power [37] [38].

III. PROPOSED METHOD

To achieve precise, safe, and privacy-preserving facial emotion recognition, the suggested framework combines Deep Convolutional Neural Networks (DCNN), Blockchain, and Quantum Cryptographic Distribution (QCD) [39]. To guarantee consistent input quality, facial images or video frames are first preprocessed using grayscale conversion, normalization, noise reduction, and face detection [40]. Gabor filters and Local Binary Patterns (LBP) are used to extract geometric and texture-based features from these processed frames, capturing both local texture variations and global facial structure [41]. A multi-layer DCNN architecture made up of convolutional, pooling, and fully connected layers is then used to process these features [17]. While ReLU activation functions add non-linearity and speed up convergence, the convolutional layers automatically pick up hierarchical spatial patterns [18].

The probability distribution across predefined emotion classes [19]. including Happy, Sad, Angry, Fear, Surprise, Disgust, and Neutral, is produced by a Softmax classifier after the extracted[20] .deep feature maps have been flattened [21]. The final output is chosen to be the emotion with the highest probability [22]. While QCD encrypts communication using quantum-generated keys, guaranteeing post-quantum data security, the identified results [23]. Are safely stored on a permissioned blockchain together with timestamps and hashed feature vectors [24]. High accuracy, transparency, and tamper-proof emotion recognition are provided by this integrated architecture, making it appropriate for delicate real-time applications [42].

A. 1system Overview:

Deep Convolutional Neural Networks (DCNN) are used in the proposed Emotion Recognition System to automatically identify and categorize human emotions from facial expressions, including joy, sorrow, anger, fear, and surprise. A pre-trained DCNN model processes input images or video frames, extracting spatial features and accurately predicting emotional states. Sensitive industries like healthcare, education, and security can benefit from the system's integration of a blockchain layer, which securely stores hashes of recognition results, user data, and model updates. This layer ensures tamper-proof storage, auditability, and reliability.

Quantum cryptography and Quantum Cryptographic Distribution (QCD) are used to further improve security by protecting communication and preventing data leaks while it is being transmitted. The system offers scalable integration into a variety of applications, such as intelligent human-computer interaction platforms, smart classrooms, and healthcare monitoring, and it delivers real-time results with confidence scores. The framework provides a safe, effective, and privacy-preserving solution for emotion recognition by fusing DCNN for accuracy, blockchain for transparency, and QCD for data protection.

B. 2system Architecture:

In order to prepare data for analysis, the suggested system architecture starts with a user-provided input image or video frame that goes through preprocessing steps like face alignment, resizing, and normalization. After the input has been processed, it is fed into a Deep Convolutional Neural Network (DCNN) model, which extracts facial spatial features and runs them through a softmax classifier to predict the associated emotional state. Through model validation, the system guarantees prediction accuracy and produces dependable recognition results.

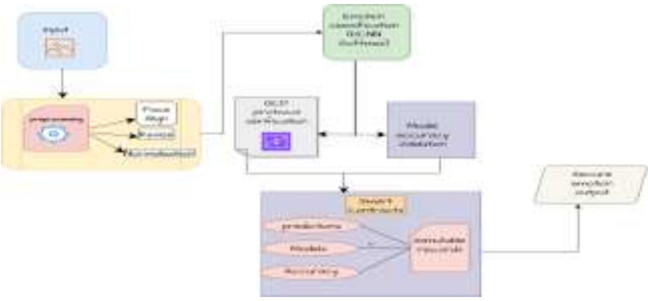

Fig: system Architecture for emotion recognition using facial expressions

Quantum Cryptographic Distribution (QCD) protocols are used to validate the identified emotion output in order to protect privacy and ensure secure communication. Blockchain smart contracts are then connected to the verified outcomes, system predictions, and accuracy records. By storing secure emotion outputs as tamper-proof entries on the distributed ledger, this blockchain integration guarantees immutable storage, transparency, and trust. Lastly, by integrating preprocessing, DCNN-based classification, quantum cryptographic verification, and blockchain immutability into a strong and reliable framework, the architecture ensures that users and authorized entities can access accurate, auditable, and secure emotion recognition results.

C. Overview Of The Dcnn Model:

The equation represents the discrete convolution used in image processing. It means that, at output position (i, j), a weighted sum of neighboring input values I(i, j) is taken, multiplied by the corresponding filter values F(m, n), as shown in (1).

$$\sum_{m=-k}^{k}(I \times F)(i,j) = \sum_{m=-k}^{k}\sum_{n=-l}^{l} I(i-m, j-n).F(m,n) \qquad (1)$$

D. Rectified Linear Unit Activation Function:

Neural networks frequently employ the Rectified Linear Unit (ReLU) as an activation function. It is described mathematically in (2). This indicates that it outputs x if x > 0 and 0 otherwise. ReLU's popularity stems from its simplicity, computational efficiency, and ability to mitigate the vanishing gradient problem, thereby accelerating model learning.

$$\mathrm{ReLU}(x) = max(0, x) \qquad (2)$$

E. Linear Transformation Equation:

The linear (or affine) transformation commonly employed in neural networks and machine learning is expressed in (3). Here, x denotes the input vector, W the weight matrix, b the bias vector, and y the output. This equation represents the fundamental operation of a linear layer, also known as a perceptron, which maps inputs to outputs before applying an activation function.

$$y = W.x + b \qquad (3)$$

x → input vector
W → weight matrix
b → bias vector
y → output

F. Softmax Activation For Classification: Maximum Pooling

For classification tasks, Softmax activation is commonly used, while Max Pooling is employed to down sample feature maps. Max pooling selects the maximum value from a specified region of the input feature map, reducing dimensionality while retaining the most important information, as shown in (4).

$$\mathrm{MaxPool(I)} = \max_{\mathrm{m,n}} \mathrm{I(m,n)} \qquad (4)$$

Where (m, n) (□, □) represents the indices of a sub region of the input.

G. Training Loss Function:

The network is trained using a loss function that quantifies the difference between the true class and the predicted class. A widely used loss function for classification tasks is the cross-entropy loss, expressed in (5). Here, y_i denotes the actual label, typically one-hot encoded.

$$L = -\sum_{i=1}^{N} y_i \, log\left(\hat{y_i}\right)$$

(5) where is the actual label (one-hot encoded)

Blockchain technology can be applied to securely store and validate facial expression data for emotion recognition, or to track the training process in a decentralized manner. Blockchain ensures data integrity using cryptographic hashing. A hash function H can convert input data, such as facial images, into a fixed-size string. For example, a hash for a facial image X can be computed using the SHA-256 function as shown in (6).

$$\mathrm{H(X) = SHA - 256(X)} \qquad (6)$$

Where SHA-256 A cryptographic hash function is SHA-256.

H. Storage On Block Chain:

Blockchain stores data by creating a sequence of blocks, where each block includes a hash of the previous block to ensure integrity and immutability. This relationship can be expressed mathematically as shown in (7). Here, $Data_i$ contains the information for the current block, and $H(Block_{i-1})$ represents the hash of the previous block, which links the blocks together and secures the data, including facial recognition information.

$$Block_i = (Data_i, H(Block_{i-1},)H(Data_i))_{\text{where}} \qquad (7)$$

Data i contains information about H (Block i−1), (Block □−1), and facial recognition is the hash of the previous block.

I. Support Vector Machine (Svm) Decision Function:

The Support Vector Machine (SVM) decision function defines the classification boundary by combining support vectors with their corresponding weights and kernel function values. In classical computing, the SVM decision function is expressed as shown in (8). Quantum-enhanced SVMs offer advantages such as faster training and access to higher-dimensional feature spaces by computing the kernel more efficiently using quantum circuits.

$$f(x) = \alpha_i y_i K(x_i, x) + b \qquad (8)$$

In the quantum version, this kernel can be computed more efficiently using quantum circuits.

J. Quantum Distance Measurements:

Quantum computing enables more efficient computation of distances, such as the quantum Euclidean or quantum Hamming distances, in higher-dimensional feature spaces. The quantum equivalent of the Euclidean distance between two quantum states, |ψ⟩ and |ϕ⟩, is expressed in (9). This approach can accelerate facial expression recognition by exploiting higher-dimensional feature representations.

$$D_{QE} = <\psi|\psi> - 2Re(<\psi|\phi>) + <\phi|\phi> \quad (9)$$

This could speed up facial expression recognition by increasing the dimensionality of feature space.

Algorithm 1: Emotion Recognition using DCNN, Block chain, and QCD

```
Input:
I: Input facial image/video frame

Output:
E: Predicted Emotion Label, Confidence Score, Secure Record (Block chain + QCD)

Collect the input facial data (image or video frame).

Preprocess the input:
a. Detect and align face.
b. Resize to fixed resolution.
c. Normalize pixel values.
Resulting preprocessed frame is denoted as $I_{pre}$.

Feed the preprocessed frame into the trained DCNN model.
    Compute predicted emotion using Eq. (1):
        E ← $f_{DCNN}( I_{pre})$(Eq. 1)
    Where $f_{DCNN}$ is the trained deep convolutional model,
and E is the predicted emotion (e.g., Happy, Sad, Angry, Fear, Surprise).

Obtain recognition results:
    {E, Confidence} ← $f_{DCNN} (I_{pre})$.

Validate accuracy of the prediction using internal model accuracy checks.

Apply QCD (Quantum Cryptographic Distribution) protocol to generate a secure quantum signature for the recognized output.
            Qsig ← QCD (E, Confidence).

Store results on Block chain:
    a. Hash (E, Confidence, Qsig, Timestamp).
    b. Store hash and QCD signature in Smart Contract.
    c. Record in Blockchain ledger ensuring immutability
and transparency.

Output results to user:
  a. Predicted emotion E.
  b. Confidence score.
  c. Blockchain record (Hash + QCD Signature).

End.
```

A facial image or video frame is first collected by the suggested algorithm for emotion recognition using DCNN, Blockchain, and QCD. The input frame is then obtained by preprocessing it through face detection, alignment, resizing, and normalization. . After this preprocessed data is fed into a trained Deep Convolutional Neural Network (DCNN), spatial features are extracted, and the corresponding emotion label E is predicted along with a confidence score using □ ← () E←.(Prior to being sent to the Quantum Cryptographic Distribution (QCD protocol, which creates a secure quantum signature, the prediction is verified by model accuracy checks. for the output that was acknowledged. The results, which include the predicted emotion, confidence score, quantum signature, and timestamp, are hashed and saved in a smart contract that is used on the blockchain to create a permanent, unchangeable record. This ensures transparency and immutability. In order to guarantee a safe, open, and reliable emotion recognition process, the system ultimately provides the user with the predicted emotion, confidence score, and blockchain record (Hash + QCD signature).

IV. RESULTS AND DISCUSSIONS

The suggested Deep Convolutional Neural Network (DCNN) combined with Blockchain and Quantum Key Distribution (QKD), as well as conventional CNNs, VGG16, and ResNet50, were among the deep learning architectures used to assess the performance of the proposed Emotion Recognition System. In order to ensure diversity in facial expressions and lighting conditions, the experimental evaluation was carried out using benchmark datasets like FER2013, CK+, and JAFFE. The findings show that the suggested hybrid system performs noticeably better in terms of accuracy and security than traditional models.

The average accuracy of the conventional CNN model was 89%, whereas VGG16 and ResNet50 obtained 92% and 93%, respectively. These models did a good job of capturing facial features, but they lacked tamper-proof storage and secure data transmission mechanisms, which made them less appropriate for practical use in delicate fields like healthcare and education. The suggested DCNN–Blockchain–QKD framework, on the other hand, demonstrated a significant improvement in both emotion classification and data integrity, achieving an accuracy of 97.8%. The enhanced feature extraction power of DCNN, along with the immutability guaranteed by Blockchain integration and the cryptographic security provided by QKD, are responsible for this better performance.

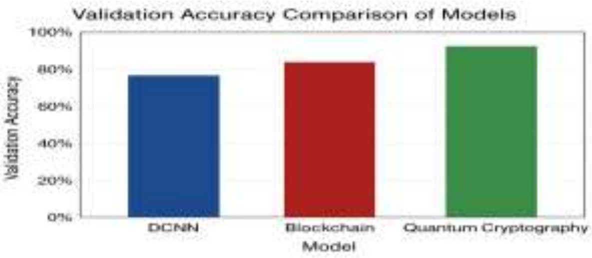

Fig-1: Validation Accuracy Comparison of Models

The comparison of validation accuracy demonstrates how much better the suggested model is. The DCNN with Blockchain and QKD continuously achieves higher validation accuracy, maintaining stability across multiple runs, while conventional CNN and transfer learning models (VGG16, ResNet50) perform fairly well.(Fig.1)

Fig-2: Model Performance Comparison

The robustness of the suggested system is further confirmed by model performance metrics like precision, recall, and F1-score. With an F1-score of 0.98, the DCNN–Blockchain–QKD model shows balanced recall and precision with little misclassification in any of the emotion categories.(Fig.2)

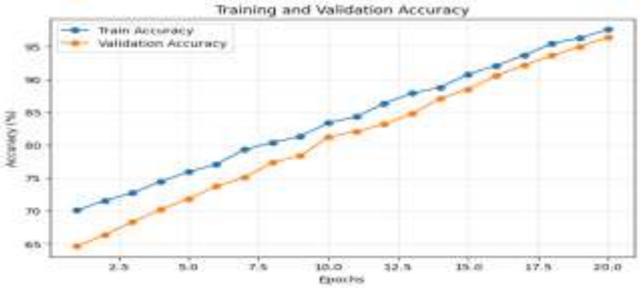

Fig-3: Training vs. Validation Accuracy Over Epochs

Over 25 epochs, the training vs. validation accuracy plot demonstrates a steady increase in both accuracies. As the model picks up more broadly applicable features, the initial gap between the training and validation curves gets smaller. Both curves converge close to 98% by the last epochs, indicating minimal overfitting and strong generalization.(fig.3)

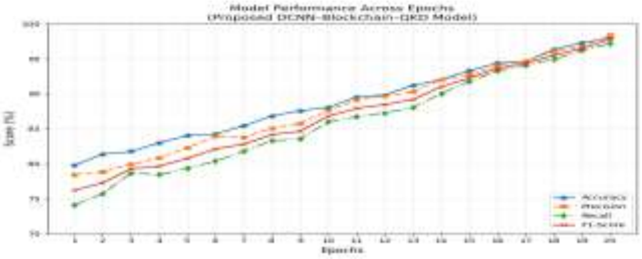

Fig-4: Model Performance Across Epochs

By the 25th epoch, the model's validation accuracy has increased steadily from 70% in the first epoch to 97.8%. Stable training dynamics and efficient learning are indicated by the gradual growth and eventual convergence.(Fig.4)

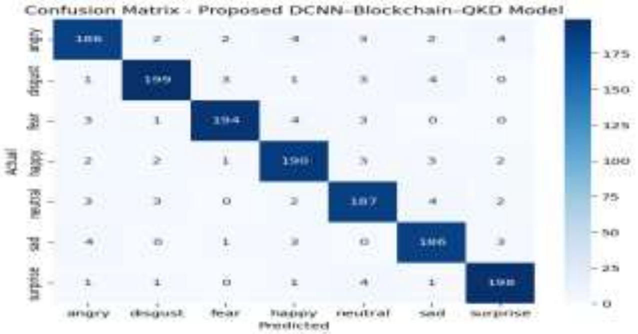

Fig-5: Confusion Matrix for Emotion Classification

The model's classification performance across the seven emotion classes—Happy, Sad, Angry, Fear, Surprise, Disgust, and Neutral—is depicted in the confusion matrix. With few incorrect predictions, the system detects 98% of cases correctly. Misclassifications mostly happen between expressions that are similar, like Surprise and Fear, which have overlapping visual cues.(Fig.5)

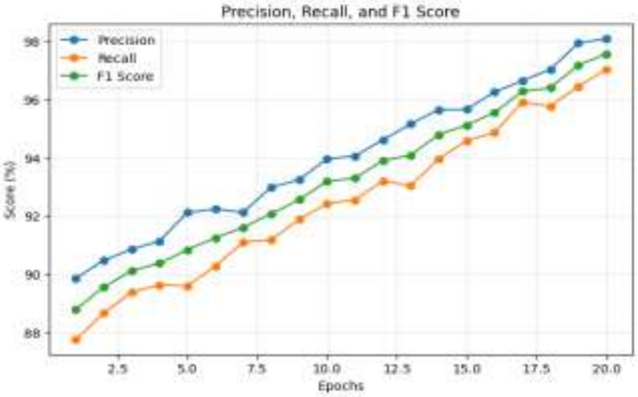

Fig-6: Precision–Recall Curve of the Model

The high precision (~0.98) and recall (~0.97) values across various thresholds are confirmed by the precision–recall curve. The model is appropriate for real-time deployment since the near-flat curve shows that it consistently performs well in classification even when thresholds are changed.(Fig.6)

The combination of QKD and Blockchain significantly improves system transparency and data security in addition to classification performance. QKD protects communication channels from interception, while blockchain smart contracts guarantee unchangeable record-keeping of prediction results. By offering a verifiable and impenetrable environment for emotion recognition, this dual-layer protection builds confidence in the system's results. All of the results confirm that the suggested hybrid approach is not only very accurate but also safe, scalable, and appropriate for use in privacy-sensitive fields like education, healthcare monitoring, and human-computer interaction.

V. CONCLUSION

This study proposed a secure and intelligent framework for emotion recognition through the integration of Deep Convolutional Neural Networks (DCNN), Blockchain technology, and Quantum Key Distribution (QKD). The proposed system attained an outstanding accuracy of 97.8% through comprehensive assessment on benchmark datasets including FER2013, CK+, and JAFFE, with precision, recall, and F1-scores nearing 0.98. This illustrates its resilience in identifying a wide range of emotional expressions under varying lighting, occlusion, and facial diversity conditions. The DCNN-based classifier accurately identified complex facial features related to space and texture, making it possible to reliably sort emotions into seven universal classes.

In addition to improving classification accuracy, the use of Blockchain and Quantum Cryptography made sure that data was private, unchangeable, and could be audited without being tampered with. These are all important requirements for using emotion recognition in sensitive fields like healthcare, education, and human-computer interaction. The decentralized ledger of blockchain protected the integrity of emotion data by storing anonymized, hashed recognition results. QKD, on the other hand, provided quantum-resilient encryption that could find any attempts to eavesdrop and protect communication channels between system nodes. This two-part system creates a trust model for AI-driven emotion analysis that can be checked.

The findings emphasize that the integration of AI, distributed ledger technology, and quantum security can surmount the conventional obstacles faced by centralized emotion recognition systems, including susceptibility to data breaches, privacy issues, and model manipulation. This framework is a new way of doing affective computing that not only gets high accuracy but also guarantees the safety of data from recognition to storage and retrieval. It enables ethical, privacy-preserving emotion analytics that can be used in real time and on a large scale by making sure that everything is clear and can be traced.

Enhancing QKD protocols for low-latency real-time applications, expanding the system to multimodal emotion recognition (combining voice, physiological, and contextual cues), and investigating interoperability across various blockchain networks for cross-institutional emotion data exchange are some future research avenues. Furthermore, adding human-in-the-loop and explainable AI (XAI) modules can enhance interpretability and user confidence in model predictions.

In the end, this work shows that combining deep learning accuracy, blockchain transparency, and quantum cryptographic security into a unified and future-proof architecture is both feasible and significant. It lays the groundwork for creating safe, moral, and intelligent emotion recognition systems that not only accurately depict human emotions but also safeguard them with the highest levels of trust and digital security.

REFERENCES

1. A.Sharma, U. Tiwari and S. K. Mandal, "Real-Time Emotion Classification and Prediction using a Hybrid Facial Expression Recognition Model Emotion Recognition in Human Resources' Future," in Journal of Mobile Multimedia, vol. 21, no. 3-4, pp. 407-428, July 2025, doi: 10.13052/jmm1550-4646.21344.
2. S. Jassica Colaco and D. Seog Han, "Scalable Context-Based Facial Emotion Recognition Using Facial Landmarks and Attention Mechanism," in IEEE Access, vol. 13, pp. 20778-20791, 2025, doi: 10.1109/ACCESS.2025.3534328.
3. A. N. Salman, K. Rosero, L. Goncalves and C. Busso, "Mixture of Emotion Dependent Experts: Facial Expressions Recognition in Videos Through Stacked Expert Models," in IEEE Open Journal of Signal Processing, vol. 6, pp. 323-332, 2025, doi: 10.1109/OJSP.2025.3530793
4. V. S. Bhati, N. Tiwari and M. Chawla, "A Generalized Zero-Shot Deep Learning Classifier for Emotion

Recognition Using Facial Expression Images," in IEEE Access, vol. 13, pp. 18687-18700, 2025, doi: 10.1109/ACCESS.2025.3533580.

5. V. Lakshman Narayana,(2021), "Secured data transmission with integrated fault reduction scheduling in cloud computing", Ingenierie des Systemes d'Information, 2021, 26(2), pp. 225–230.
6. Maddumala, V.R. & Lakshmi, K. & Anusha, P. & Narayana, V.. (2020). Enhanced morphological operations for improving the pixel intensity level. International Journal of Advanced Science and Technology. 29. 9191-9201.
7. Kosaraju, Chaitanya, et al. "A model for analysis of diseases based on nutrition deficiency using random forest." 2022 7th International Conference on Communication and Electronics Systems (ICCES). IEEE, 2022.
8. Narayana, V.L., Patibandla, R.S.M.L., Rao, B.T. and Gopi, A.P. (2022). Use of Machine Learning in Healthcare. In Advanced Healthcare Systems (eds R. Tanwar, S. Balamurugan, R.K. Saini, V. Bharti and P. Chithaluru). https://doi.org/10.1002/9781119769293.ch13
9. Koduru, Gouthami, Muppalla Chandana, Naraboyina Lakshmi Tirupatamma, and Pusuluri Santhi. "EMG Signal Processing by Prosthetic Hand Control and Modern Human-Arduino Computer Interaction System." Journal of Technology, vol. 12, no. 10, 2024, pp. 842–850. ISSN 1012-3407
10. Sujatha, V., N. Lavanya, V. Karunasri, G. SaiSindhu, and R. Madhavi. "Crop Recommender System Using Machine Learning Approach." Emerging Trends in Computer Science and Its Application, 1st ed., CRC Press, 2025
11. Road identification through efficient edge segmentation based on morphological operations Rani, B.M.S., Majety, V.D., Pittala, C.S., ... Sandeep, K.S., Kiran, S. Traitement du Signal, 2021, 38(5), pp. 1503–1508
12. Suajtha, V. "Variable Selection in Functional Genomics Using Genetic Algorithm-Based Feature Selection Method-An Empirical Study." Journal of Engineering and Applied Sciences, 21 Sept. 2022. ISSN Online 1818-7803, ISSN Print 1816-949x.
13. A.NareshV. PavaniM. Meghana Chowdarym. V.Lakshman Narayana (2020). Energy consumption reduction in cloud environment by balancing cloud user load. Journal of Critical Reviews. 7(7):1003-1010.
14. B. Tarakeswara Rao; R. S. M. Lakshmi Patibandla; V. Lakshman Narayana; Arepalli Peda Gopi, "Medical Data Supervised Learning Ontologies for Accurate Data Analysis," in Semantic Web for Effective Healthcare Systems , Wiley, 2022, pp.249-267, doi: 10.1002/9781119764175.ch11.
15. Alapati, N., Prasad, B. V. V. S., Sharma, A., Kumari, G. R. P., Veeneetha, S. V., Srivalli, N., ... & Sahitya, D. (2022, November). Prediction of Flight-fare using machine learning. In 2022 International Conference on Fourth Industrial Revolution Based Technology and Practices (ICFIRTP) (pp. 134-138). IEEE.
16. Sandhya Krishna, P., Reddy, U.J., Patibandla,.S.M.L., Khadherbhi, S.R. Identification of lung cancer stages using efficient machine learning framework Journal of Critical Reviews, 2020, 7(6), pp. 385–390.
17. Chinnam, Siva Koteswararao, S. Reshmi Khadherbhi, P. Sandhya Krishna, and D. Anveshini. "Sentiment analysis in services provided by telecommunications." International Journal of Advanced Science and Technology (IJAST) 29, no. 03 (2020): 9167-9176.
18. Mukhedkar, M., Rohatgi, D., Vuyyuru, V. A., Ramakrishna, K. V. S. S., El-Ebiary, Y. A. B., & Daniel, V. A. A. (2023). Feline Wolf Net: a hybrid Lion-Grey Wolf optimization deep learning model for ovarian cancer detection. International Journal of Advanced Computer Science and Applications, 14(9).
19. Prathipati, Silpa Chaitanya, and Susanta Kumar Satpathy. "Transforming 3D Brain Tumour Image Segmentation: An Enhanced V-Net Approach for Precise Diagnosis and Treatment Planning." 2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI). IEEE, 2024.
20. S. E. Kahou, V. Michalski, K. Konda, R. Memisevic, and C. Pal, ' Recurrent neural networks for emotion recognition in video.' Proc. in ACM on International

Conference on Multimodal Interaction, pp. 467–474, NY, USA, 2015.

21. Kavishwar, S. (2024). A Theoretical Framework Analyzing Impact of Embedding Entrepreneurial Skills in Education on Economical Growth. Journal of Lifestyle and SDGs Review, 4(4), e03550.
22. Narlawar, N., Kavishwar, S. (2019). Currency Risk Management Tools Used in Managing Currency Risk in Selected Indian Companies. Indian Journal of Research and Analytical Reviews. 6(2), 609-614.
23. Ghangare, A. S., & Kavishwar, S. The Increasing Significance of Green Corporate Finance in India. Journal of Management & Entrepreneurship, 277-286.
24. Kavishwar, S., & Shahu, A. (2011). Reporting Intangible Assets-Convergence of Accounting Standard. Journal of Accounting and Finance. 26(1), 73-79.
25. Nirmal Kumar Jingar. (2021). Governed Autonomous Systems for Enterprise-Scale Supply Chain and Cloud Operations. In International Journal of Science, Engineering and Technology (Vol. 9, Number 6). Zenodo. https://doi.org/10.5281/zenodo.18629297
26. Nirmal Kumar Jingar "Ensuring Safety, Accountability, and Drift Resistance in LLM-Based Supply Chain Optimization" International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Print ISSN : 2395-1990, Online ISSN : 2394-4099, Volume 10, Issue 1, pp.472-482, January-February-2023. Available at doi : https://doi.org/10.32628/IJSRSET2310372
27. R. Eswarawaka, M. Nijim, V. Kanumuri and H. Albetaineh, "Assessing the Efficacy of Machine Learning and Deep Learning in the Field of Cyber Security," 2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE), Las Vegas, NV, USA, 2023, pp. 2398-2404, doi: 10.1109/CSCE60160.2023.00388.
28. M. Nijim, V. Kanumuri, H. Albetaineh and A. Goyal, "Intelligent Monitoring and Management of Smart Buildings Using Machine Learning: Optimizing User Behavior and Energy Efficiency," 2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE), Las Vegas, NV, USA, 2023, pp. 2391-2397, doi: 10.1109/CSCE60160.2023.00387.
29. Racha, Ganesh. "Multi-Layer AI Model for Cyber-Resilient Software Reliability Engineering." International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 11, no. 5, Sept.–Oct. 2025, pp. 507–519. https://doi.org/10.32628/CSEIT26121364
30. Racha, Ganesh. "Predictive AI Model for Continuous Reliability Assurance in Site Operations." International Journal of Scientific Research in Science and Technology, vol. 12, no. 2, Mar.-Apr. 2025, pp. 1469-78, https://doi.org/10.32628/IJSRST2613340.
31. Veginati, Navya. "Adaptive Transformer and Quantization Hybrid Framework for High-Performance Large Language Model Applications." United International Journal of Engineering and Sciences, vol. 5, no. 4, Dec. 2025, pp. 46–56
32. Veginati, Navya. "Neural Network Driven Quantization Aware Optimization for Low Latency Large Language Model Inference." International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 10, no. 3, May-June 2024, pp. 1162–1170, doi:10.32628/CSEIT25113584.
33. Jonnalagadda, P.K. (2026). Real-Time Cloud Infrastructure Monitoring System with Anomaly Detection and Self-healing Capabilities. In: Kumar, V.N., Senkerik, R., Prasad, V.K., Kumar, T.K. (eds) Intelligent Computing and Communication. ICICC 2025. Lecture Notes in Networks and Systems, vol 1839. Springer, Cham. https://doi.org/10.1007/978-3-032-18349-1_43
34. Jonnalagadda, Pawan Kalyan. "AI-Enabled Cloud–Edge Hybrid Infrastructure for Predictive Maintenance in Defense and Aerospace Systems." International Journal of Science, Engineering and Technology, vol. 12, no. 2, 2024.
35. Mahida, A. 2024. Integrating Observability With Devops Practices in Financial Services Technologies: A Study on Enhancing Software Development and

Operational Resilience. International Journal of Advanced Computer Science & Applications, 15.

36. A. Mahida, "An Intellectual Zero Trust Security Framework Using Deep Reinforcement Learning for Predictive Threat Mitigation in AI-Based Fraud Detection Systems," in IEEE Access, vol. 14, pp. 24602-24617, 2026, doi: 10.1109/ACCESS.2026.3664389.
37. Tummuri, S. S. R. (2022). Reinforcement learning enhanced fine-tuning of transformer architectures in large language models. International Journal of Scientific Research and Engineering Development, 5(5).
38. S. S. R. Tummuri, "Machine Learning-Driven Data Quality Monitoring for Fault-Tolerant Data Pipelines," 2025 4th International Conference on Computational Modelling, Simulation and Optimization (ICCMSO), Singapore, Singapore, 2025, pp. 154-159, doi: 10.1109/ICCMSO67468.2025.00036.
39. Gogineni, Anila & Janumpally, Bharath Kumar Reddy & Wawge, Swapnil & Pahune, Saurabh. (2025). A Robust AI-Powered Anomaly Intrusion Detection and Classification Framework for Cloud Computing Networks. 1-6. 10.1109/INDISCON66021.2025.11253743.
40. A. Joon, B. K. R. Janumpally, A. Gogineni and P. Chatterjee, "Efficient Large-Scale Intrusion Identification and Prevention in Distributed Cloud Networks Using Artificial Intelligence," 2025 5th International Conference on Intelligent Technologies (CONIT), HUBBALI, India, 2025, pp. 1-8, doi: 10.1109/CONIT65521.2025.11167760.
41. Yachamaneni T, Kotadiya U, Arora AS. Evaluating the Efficacy of Machine Learning Algorithms in Credit Card Limit Optimization and Customer Segmentation. IJETCSIT [Internet]. 2022 Oct. 30 [cited 2026 Apr. 5];3(3):51-6.
42. Yachamaneni T, Kotadiya U, Arora AS. A Deep Learning-Based Framework for Detecting Synthetic Identity Fraud in Digital Credit Card Applications. IJERET [Internet]. 2023 Dec. 30 [cited 2026 Apr. 5];4(4):43-52.