Hybrid Deep Learning Model For Early Fault Detection In Energy-Intensive Tablet Press Equipment: MLP–1D CNN Fusion For EMIS Applications

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Abstract- *Fault detection in pharmaceutical tablet press equipment is crucial for ensuring product quality, minimizing downtime, and reducing energy consumption in energy-intensive manufacturing environments. This study presents a hybrid deep learning model, namely MLP–1D CNN FaultNet, which integrates a Multilayer Perceptron (MLP) and a one-dimensional Convolutional Neural Network (1D CNN). The architecture employs parallel branches to capture both global statistical dependencies and localized feature patterns. The MLP branch models global feature interactions, while the 1D CNN branch extracts spatial correlations through convolutional operations. The learned representations are fused in a dedicated layer and further refined using dense layers with dropout and batch normalization to improve generalization. The final classification layer performs fault detection effectively. Experimental results indicate that the hybrid model outperforms standalone MLP and CNN models in terms of accuracy, precision, recall, and F1-score. Therefore, the architecture is suitable for real-time monitoring, predictive maintenance, and energy-aware fault management in pharmaceutical manufacturing systems.*

Keywords: Fault detection, deep learning, hybrid model, 1-D CNN, MLP, fusion

I. INTRODUCTION

Fault detection in pharmaceutical tablet press equipment is a critical aspect of modern manufacturing, where even minor faults can compromise product quality, disrupt production schedules, and lead to significant energy inefficiencies. As pharmaceutical manufacturing continues to expand and regulatory requirements become more stringent, early and accurate fault detection has emerged as a key component of intelligent equipment monitoring and predictive maintenance.

Fault detection in such systems is important from technical, economic, and operational perspectives. Technically, these machines operate under tightly controlled conditions, where even minor faults can degrade product quality and introduce noise or errors into high-dimensional operational data. Economically, undetected faults can result in costly downtime, material wastage, and increased energy consumption. From an operational standpoint, faults can compromise entire production batches, reduce equipment lifespan, and affect process reliability. Early fault detection enables predictive maintenance, minimizes unplanned interruptions, and supports energy-efficient manufacturing.

Existing approaches often rely on either Multilayer Perceptrons (MLPs) or Convolutional Neural Networks (CNNs) in isolation, limiting their ability to capture both global statistical dependencies and localized feature patterns in complex operational data. Moreover, many studies focus on general industrial environments, with limited attention to the specific constraints of pharmaceutical equipment, such as strict regulatory compliance, high throughput, and energy sensitivity. In addition, there is a need for modular and interpretable architectures that can be deployed in real-time and adapted to both binary and multiclass fault detection scenarios.

To address these limitations, this study presents a hybrid deep learning architecture that integrates MLP and 1-D CNN branches in a parallel configuration. This design enables the model to learn complementary representations—capturing both global statistical relationships and localized spatial patterns—within a unified framework. The extracted features are fused and further refined using fully connected layers with dropout and batch normalization, resulting in a modular and deployment-ready model.

The hybrid architecture, referred to as MLP–1D CNN FaultNet, combines the strengths of both MLP and CNN models. The MLP branch captures global feature interactions, while the 1-D CNN branch focuses on extracting localized patterns and correlations. By processing the same input through both branches simultaneously, the model learns complementary feature representations that enhance classification performance. This fusion improves generalization and robustness, particularly in noisy and high-dimensional environments.

Overall, the architecture addresses the limitations of standalone models by integrating both global and local feature learning mechanisms. It eliminates the need for extensive manual feature engineering, improves fault detection accuracy, and supports both binary and multiclass classification tasks. Its modular design enables easy integration into existing monitoring systems, while its computational efficiency supports real-time deployment. The model is particularly suitable for energy-aware pharmaceutical manufacturing, where early fault detection, regulatory compliance, and operational continuity are essential.

II. LITERATURE REVIEW

Neupane et al. [1] proposed a deep learning-based fault detection method for smart manufacturing environments, focusing on bearing fault classification using time-sequence data from the Case Western Reserve University (CWRU) bearing dataset. Their approach employed a 1-D convolutional neural network (CNN), demonstrating state-of-the-art accuracy even with limited training data. Through comparative analysis with a 2-D CNN model, they showed that 1-D CNNs are more effective and computationally efficient for temporal signal processing. The model achieved high precision, recall, and F1-score, outperforming several complex algorithms in bearing fault diagnosis, and underscored the growing importance of intelligent fault detection methods in Industry 4.0-enabled smart factories.

Wang et al. [2] proposed a deep learning-based observer for fault detection in industrial robot motor drive systems, addressing the challenges posed by nonlinear dynamics and complex operating conditions. Their architecture integrates convolutional neural networks (CNN) for dynamic feature extraction and long short-term memory (LSTM) networks for time-sequential prediction. Trained on normal samples, the CNN-LSTM observer enables online fault detection through residual analysis. Applied to a brushless DC motor drive system, the method demonstrated strong fault detection capabilities, validating its effectiveness for real-time monitoring in intelligent manufacturing environments.

Eang et al. [3] proposed a hybrid deep learning framework combining Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to improve predictive maintenance and fault detection in DC motor drives of industrial robots. Their CNN-RNN model processes sensor data—such as air temperature, process temperature, and rotational speed—to extract dynamic features and perform sequential analysis for early fault prediction. Compared to CNN-LSTM and other conventional methods, the model achieved superior accuracy and precision while maintaining a simpler architecture and lower computational complexity, making it a practical solution for real-time fault diagnosis in smart manufacturing environments.

Al-Andoli et al. [4] proposed a parallel ensemble model integrating hybrid machine learning and deep learning techniques for fault detection and diagnosis (FDD) in industrial machinery. Their architecture comprises two base learners and a meta-learner, executed on a parallel processing platform to enhance computational efficiency. The base learners combine Back-Propagation (BP) and Particle Swarm Optimization (PSO) to leverage both local and global optimization capabilities. Validated on benchmark datasets (CWRU and MAFaulD), the model achieved high accuracy rates of 98.45% and 99.79%, respectively, while significantly reducing computation time. These results highlight the model's effectiveness and scalability for real-world FDD applications in industrial environments.

Souza et al. [5] proposed a predictive maintenance model based on Convolutional Neural Networks (PdM-CNN) for early fault detection and classification in rotating industrial machinery. Their approach utilizes data from a single vibration sensor mounted on the motor-drive end bearing—an industry-standard configuration—to classify faults under varying rotational speeds, load levels, and fault severities. The PdM-CNN model achieved high accuracy rates of 99.58% and 97.3% across two publicly available datasets, demonstrating its effectiveness in reducing sensor acquisition costs and supporting digital transformation in Industry 4.0 environments.

Xu et al. [6] developed a hybrid deep learning model combining Convolutional Neural Networks (CNN) and deep forest (gcForest) to improve bearing fault detection accuracy in industrial applications. To address the limitations of existing models that often overlook fault feature extraction, their method converts vibration signals into time-frequency images using continuous wavelet transform (CWT). CNN is employed to extract intrinsic fault features, which are then classified by gcForest. The model achieved higher detection accuracy than standalone CNN and gcForest approaches, demonstrating its practical potential for intelligent fault diagnosis.

Adel et al. [7] proposed an intelligent method for automatic detection, identification, and classification of gear faults in rotating machinery, addressing the challenge of overlapping frequency signatures and variable load-speed conditions. Their approach integrates Modified Orthogonal Discrete Wavelet Packet Transform (MODWPT) for signal decomposition, entropy for feature extraction, and a Multi-Layer Perceptron Neural Network (MLPNN) for classification. Evaluated on gearbox bench test data with six gear states under varying operational conditions, the method demonstrated high efficiency in fault diagnosis, offering a robust solution for complex gear fault classification tasks.

Alqunun et al. [8] introduced an advanced method for bearing fault detection in rotating machinery by integrating multi-feature extraction, optimized feature selection, and deep learning classification. Their approach employs continuous wavelet transform (CWT) and convolutional neural networks (CNN) for feature extraction from the CWRU Fault Bearing Dataset, followed by hyperparameter tuning via Tree-Structured Parzen Estimators (TPE). The ResNet-50-SVM hybrid model achieved an accuracy of 95.51%, demonstrating the method's effectiveness for predictive and preventive maintenance in industrial applications.

Bharatheedasan et al. [9] proposed a hybrid fault diagnosis framework combining a feedforward Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) network to enhance fault detection and remaining useful life (RUL) prediction of rolling bearings. Their approach utilizes voltage signals recorded under various fault conditions, including inner and outer raceway defects, which are pre-processed through normalization and band-pass filtering. Short-Time Fourier Transform (STFT) is applied to generate time-frequency representations for transient feature analysis. The hybrid MLP-LSTM model captures both non-linear relationships and temporal dependencies, outperforming traditional methods such as FCN, SVM, Decision Tree, KNN, LSTM, and CNN-BILSTM. Achieving an accuracy of 99.9%, sensitivity of 98.90%, and specificity of 98.16%, the model demonstrates strong potential for predictive maintenance in industrial environments.

Borandag et al. [10] investigated software fault prediction using both machine learning (ML) and deep learning (DL) techniques, leveraging the SFP XP-TDD dataset generated from three distinct software projects. Their study trained five widely used classifiers and their Rotation Forest ensemble variants, comparing performance across multiple datasets, including Eclipse and Apache Active MQ. While prior literature emphasized ML-based fault prediction and feature selection strategies, few studies explored DL approaches due to limited sample sizes and low test success rates. This research demonstrated that DL models—particularly those incorporating recurrent neural networks (RNNs)—outperformed ML algorithms on large datasets, offering a statistically validated advancement in software fault prediction.

Alkhanafseh et al. [11] proposed a novel Recurrent Neural Network (RNN) architecture combining Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Fully Connected (FC) layers to classify motor faults using time-series data. Their model targets ten fault categories from the Machinery Fault Database (MaFaulDa), including various misalignments, imbalances, and bearing defects. Without employing data augmentation, the model achieved train-validation-test accuracies of 99.87%, 99.599%, and 99.48%, respectively. These results underscore the model's robustness and precision, offering early fault detection and intelligent alerting capabilities for predictive maintenance in industrial electrical systems.

Seba et al. [12] proposed a proactive two-stage deep learning framework for IoT sensor fault prediction and classification. Using the Intel Lab dataset, a CNN-LSTM model forecasts sensor values, which are then classified by a CNN-MLP into fault types: bias, drift, random, and poly-drift. The CNN-LSTM achieved a MAE of 2.0957, while the CNN-MLP reached an average classification accuracy of 98.21%, outperforming baseline models. This approach enables early fault anticipation, enhancing reliability and maintenance efficiency in IoT systems.

Alhanaf et al. [13] addressed fault detection challenges in smart grids by proposing three deep learning models—CNN, LSTM, and hybrid CNN-LSTM—targeting line fault identification, fault classification, and fault location estimation. Their approach processes voltage and current signals from multiple network points, with CNN extracting features and LSTM refining fault predictions. The models demonstrated superior accuracy and robustness compared to existing methods.

Alsumaidaee et al. [14] proposed a hybrid 1-D-CNN-LSTM model for fault detection in medium voltage (MV) switchgear, leveraging both time domain (TD) and frequency domain (FD) data. Their approach processes operational signals to classify faults such as arcing, tracking, corona, and mechanical anomalies. The model achieved 100% accuracy for most fault types and 98.4% accuracy for corona faults in the TD, demonstrating strong spatial-temporal learning capabilities. This method offers a reliable and efficient solution for enhancing switchgear safety and fault diagnosis in industrial power systems.

Zabin et al. [15] introduced a hybrid deep transfer learning architecture combining DCNN and LSTM layers, enhanced by Hilbert transform-based 2D images, for industrial fault diagnosis. Their model effectively captured spatial and temporal features from three benchmark audio fault datasets under varying loads and noise conditions. Achieving an average F1 score of 0.998 and significantly reducing training epochs, the approach outperformed existing methods in accuracy and robustness across diverse industrial environments.

Wu et al. [16] proposed a hybrid LSTM-KLD model for fault detection in wind turbines, integrating deep learning with Kullback-Leibler divergence to enhance diagnostic accuracy. Applied to turbines with gearbox bearing and generator winding faults, the model achieved detection accuracies of 94% and 92%, respectively. It also demonstrated the ability to distinguish alarms from actual faults, offering early warning capabilities. Compared to three baseline machine learning methods, the hybrid approach showed superior performance in fault identification and condition monitoring.

Venkatasubramanian et al. [17] proposed a deep learning-based framework for fault detection in industrial IoT (IIoT) systems, leveraging real-time sensor data and advanced preprocessing techniques such as denoising, missing data imputation, and outlier detection. Cleaned data were fused using direct fusion methods and analyzed using models like PropensityNet, DNN, and CNN-LSTM. Evaluated on the Case Western Reserve University (CWRU) dataset, the approach demonstrated strong accuracy and efficiency, highlighting its viability for real-time fault diagnosis in IIoT environments.

Fallah et al. [18] proposed a unified framework that integrates fault diagnosis via CNN-LSTM with energy optimization through Deep Q-Networks (DQN) for intelligent IIoT systems. Their model demonstrated high classification accuracy and resilience to incomplete data, while the DQN scheduler achieved significant energy savings without violating task constraints. Validated on real-world industrial datasets, the framework outperformed conventional methods in both diagnostic precision and operational efficiency, offering a scalable solution for predictive maintenance and smart energy control in next-generation manufacturing.

III. METHODOLOGY

This section presents the dataset specifications, modeling strategy, and architectural framework adopted for fault prediction. It further elaborates on the supervised hybrid design and its integration with labeled operational data.

Dataset

The dataset [19] used for this study is a synthetic binary classification dataset sourced from Kaggle, designed to simulate tablet press machine operations and support fault detection. It contains seven features, with a total of 3,8147 instances.The features include Pressure, Temperature, Speed, Vibration, Humidity, Maintenance, and Failure. Here the feature Failure serves as the binary target label.

Data Preprocessing

The dataset underwent a structured preprocessing pipeline. Each record in the dataset corresponds to an operational instance of tablet press equipment, comprising multiple sensor-derived features and a binary fault label.

Feature-Label Separation

The target variable “Failure” was extracted and treated as the binary classification label. All remaining columns were considered as input features. The label has two values namely 0 and 1 where 0 indicates “No fault” and 1 denotes a “Fault” condition

Train-Test Partitioning

To facilitate model evaluation, the dataset was partitioned into training and test subsets using an 80:20 split. Stratified sampling was applied to maintain the original class proportions across both subsets. Consistent representation of fault conditions were ensured during training and evaluation phases.

Feature Normalization

All input features were standardized using z-score normalization through StandardScaler implementation from scikit-learn. This transformation centers each feature around zero mean and unit variance, which is essential for stable gradient descent and improved convergence in neural network training.

Model Architecture

To evaluate the effectiveness of deep learning approaches for fault detection in tablet press equipment, three distinct architectures were implemented and compared: a baseline Multilayer Perceptron (MLP), a one-dimensional Convolutional Neural Network (CNN), and hybrid MLP– 1D CNN FaultNet model. Each model was designed to operate on standardized data and trained using identical optimization settings to ensure fair comparison.

Baseline MLP Architecture

The baseline model employed in this study is a Multilayer Perceptron (MLP), designed to capture global feature interactions across the standardized sensor inputs. The architecture consists of a sequence of fully connected layers with progressively decreasing dimensionality, typically structured as Dense(128), Dense(64), and Dense(32), each followed by activation functions such as LeakyReLU or ReLU to introduce non-linearity. Batch normalization is applied to stabilize learning and accelerate convergence, while dropout regularization is incorporated to mitigate overfitting and enhance generalization. The final output layer comprises a single neuron with sigmoid activation, producing a probability score for binary fault classification. This architecture treats all input features uniformly, enabling the model to learn holistic representations of operational behavior without relying on spatial locality. While structurally simpler than convolutional or hybrid models, the MLP serves as a strong baseline for evaluating the effectiveness of deep learning in fault detection tasks.

1-D CNN Architecture

The 1-D Convolutional Neural Network (CNN) architecture employed in this study is designed to extract localized patterns and spatial dependencies across sensor features by treating the input as a one-dimensional sequence. The standardized feature vector is reshaped into a tensor of shape (d,1)(d, 1), enabling the application of 1-D convolutional filters that slide across adjacent features. The model comprises two convolutional layers with progressively reduced filter sizes, each followed by batch normalization to stabilize training and improve convergence. A global max pooling layer is applied to retain the most salient activations, effectively summarizing the learned feature maps into a compact representation. This output is then passed through a dense layer with sigmoid activation to produce a binary fault classification. By focusing on local feature interactions, the CNN architecture is particularly effective in capturing subtle fault signatures that may not be evident through global analysisalone, offering a complementary perspective to fully connected models in fault detection tasks.

Hybrid Methodology

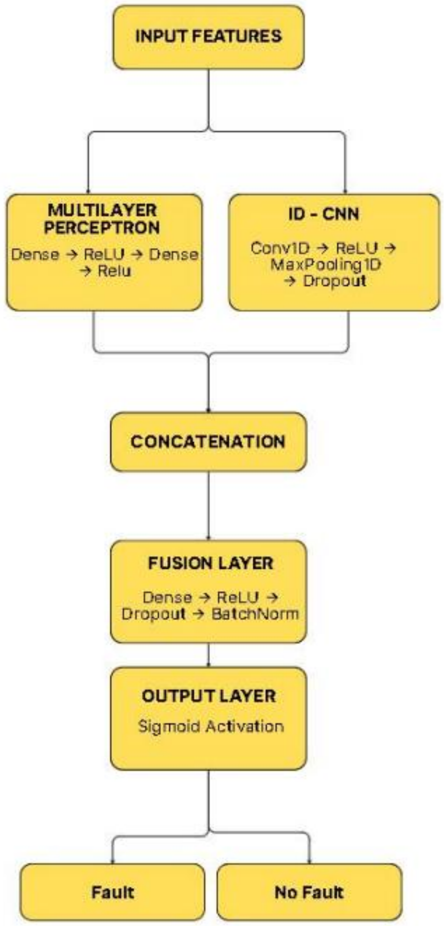
The hybrid fault detection model (MLP-1D CNN FaultNet) adopts a hybrid deep learning architecture that integrates a Multilayer Perceptron (MLP) and a one-dimensional Convolutional Neural Network (CNN) in parallel to enhance fault detection performance. The MLP branch processes the standardized feature vector through a series of fully connected layers with LeakyReLU activations, batch normalization, and dropout regularization, enabling the extraction of global feature interactions across all sensor inputs. Simultaneously, the CNN branch reshapes the input into a one-dimensional sequence and applies convolutional layers with small kernel sizes to capture localized patterns and spatial dependencies among adjacent features, followed by batch normalization and global max pooling to retain the most salient activations. The outputs of both branches are concatenated and passed through a fusion layer comprising dense units, LeakyReLU activation, batch normalization, and dropout, culminating in a sigmoid-activated output neuron for binary classification. This architecture leverages the complementary strengths of MLP and 1-D CNN components, allowing the model to learn both holistic and localized representations of operational behavior, thereby improving its ability to detect subtle and diverse fault signatures in real-world sensor data.The architecture of this hybrid model is depicted in the Fig. 1.

Evaluation metrics

To assess the performance of the proposed fault detection models, four standard classification metrics were employed: accuracy, precision, recall, and F1- score.These These metrics provide a comprehensive assessment of fault detection and classification effectiveness.The evaluation results of the three models based on standard performance metrics are presented in Table I.

TABLE I. Results Comparison

Metrics	**1-D CNN**	**MLP**	**MLP-1D CNN FaultNet**
Accuracy	96.20	97.64	98.69
Recall	92.39	95.28	97.38
Precision	100	100	100
F1 Score	96.04	97.58	98.67



Hybrid Architecture

IV. RESULTS AND DISCUSSION

The experimental results clearly demonstrate that the proposed hybrid fault detection model MLP-1D CNN FaultNet significantly outperformed both standalone MLP and CNN architectures across all key evaluation metrics, establishing its superiority for fault detection in pharmaceutical tablet press equipment. The hybrid model achieved an accuracy of 98.69%, precision of 100%, recall of 97.38%, and an F1-score of 98.67%, indicating near-perfect classification performance. In contrast, the MLP model yielded an accuracy of 97.64% and recall of 95.28%, while the 1D CNN model attained an accuracy of 96.2% and recall of 92.39%. The comparative bar graphs illustrating the performance of the three models across key metrics are presented in Fig. 2 (Accuracy), Fig. 3 (Recall), Fig. 4 (Precision), and Fig. 5 (F1-score).Although all models achieved perfect precision—reflecting zero false positives—the hybrid model's substantially higher recall and F1-score underscore its enhanced ability to detect true fault cases without sacrificing generalization. This is particularly critical in industrial fault detection, where missed faults can lead to equipment degradation, compromised product quality, and increased energy consumption. The hybrid architecture's performance advantage stems from its parallel integration of MLP and 1-D CNN branches, which enables the model to capture both global statistical dependencies and localized spatial patterns within the sensor data. The MLP branch effectively models cross-feature interactions, while the CNN branch leverages convolutional filters to extract temporal and spatial correlations. These complementary representations are fused and refined through dense layers equipped with dropout and batch normalization, which mitigate overfitting and enhance generalization. This modular design not only improves classification robustness but also supports interpretability and ease of deployment in real-time monitoring systems.

From a practical standpoint, the hybrid model is well-suited for predictive maintenance and energy-aware fault management in pharmaceutical manufacturing, where early and accurate fault detection is essential for minimizing downtime and ensuring consistent product quality. Its high recall ensures that fault conditions are reliably identified, while its perfect precision prevents unnecessary maintenance interventions. These characteristics make the model a strong candidate for integration into Energy Management and Information Systems (EMIS), enabling intelligent decision-making and sustainable operations in industrial IoT environments. Overall, the hybrid model offers a defensible, high-performing, and scalable solution for fault detection, with clear advantages over conventional deep learning baselines.

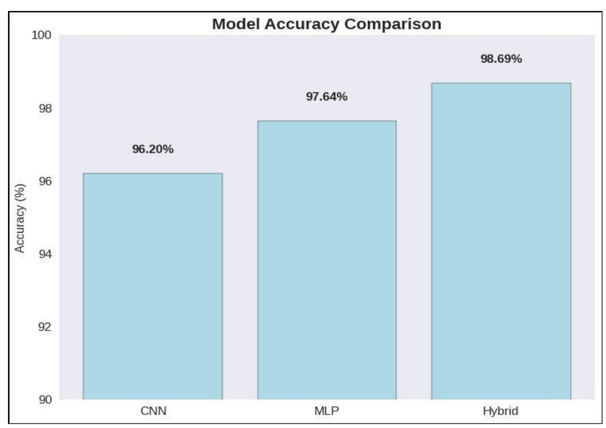


Fig. 2 Accuracy Comparison

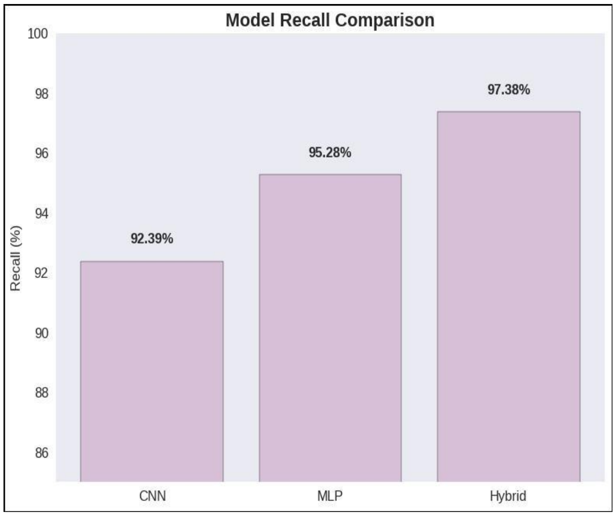


Fig. 3 Recall Comparison

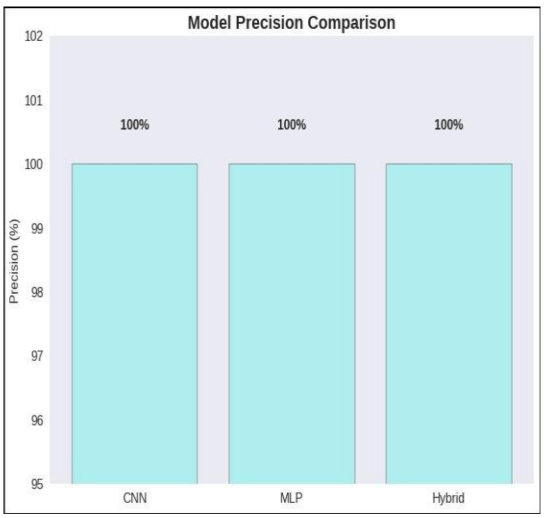


Fig. 4 Precision Comparison

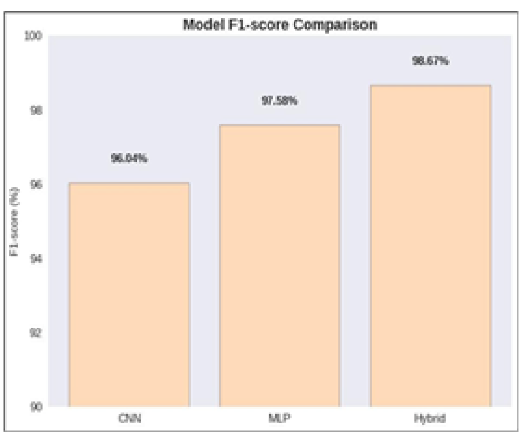


Fig. 5 F-1 Score Comparison

V. CONCLUSION

In conclusion, this study presents a robust hybrid deep learning architecture for fault detection in pharmaceutical tablet press equipment, combining the strengths of Multilayer Perceptron (MLP) and 1-D Convolutional Neural Network (CNN) branches. The proposed model effectively captures both global feature dependencies and localized spatial patterns, enabling accurate and interpretable fault classification from operational sensor data. Its modular design supports scalability and integration into industrial IoT pipelines, while maintaining computational efficiency suitable for real-time deployment. Empirical results demonstrate that the hybrid model consistently outperforms standalone MLP and 1-D CNN baselines, achieving an accuracy of 98.69%, recall of 97.38%, and F1- score of 98.67%, with perfect precision. These metrics validate the model's reliability, generalization capability, and practical applicability in energy-intensive manufacturing environments. The architecture's ability to balance performance with interpret-ability makes it a strong candidate for predictive maintenance, anomaly detection, and energy-aware fault management across diverse industrial assets. Beyond its immediate application, the model offers a defensible foundation for future research. Potential extensions include adaptation to multi-class fault scenarios, incorporation of temporal dynamics through recurrent or attention- based modules, and integration with Energy Management and Information Systems (EMIS) for holistic monitoring. More complex architectures—such as Transformer-CNN hybrids, graph neural networks, or domain-specific feature fusion frameworks—may further enhance fault localization and cross-domain generalization. Real-world deployment in live production settings, coupled with continuous learning from streaming data, represents a promising direction for scaling intelligent fault detection in smart manufacturing ecosystems.

REFERENCES

[1] Neupane, D., Kim, Y., Seok, J., Hong, J.: CNN-based fault detection for smart manufacturing. Applied Sciences 11(24), 11732 (2021)

[2] Wang, T., Zhang, L., Wang, X.: Fault detection for motor drive control system of industrial robots using CNN-LSTM-based observers. CES Trans. Electr. Mach. Syst. 7(2), 144–152 (2023)

[3] Eang, C., Lee, S.: Predictive maintenance and fault detection for motor drive control systems in industrial robots using CNN-RNN-based observers. Sensors 25(1), 25 (2024)

[4] Al-Andoli, M.N., Tan, S.C., Sim, K.S., Seera, M., Lim, C.P.: A parallel ensemble learning model for fault detection and diagnosis of industrial machinery. IEEE Access 11, 39866–39878 (2023)

[5] Souza, R.M., Nascimento, E.G., Miranda, U.A., Silva, W.J., Lepikson, H.A.: Deep learning for diagnosis and

classification of faults in industrial rotating machinery. Comput. Ind. Eng. 153, 107060 (2021)

[6] Xu, Y., Li, Z., Wang, S., Li, W., Sarkodie-Gyan, T., Feng, S.: A hybrid deep-learning model for fault diagnosis of rolling bearings. Measurement 169, 108502 (2021)

[7] Adel, A., Hand, O., Fawzi, G., Walid, T., Chemseddine, R., Djamel, B.: Gear fault detection, identification and classification using MLP neural network. In: Recent Advances in Structural Health Monitoring and Engineering Structures: Select Proceedings of SHM and ES 2022, pp. 221–234. Springer Nature Singapore, Singapore (2022)

[8] Alqunun, K., Bechiri, M.B., Naoui, M., Khechekhouche, A., Marouani, I., Guesmi, T., Alshammari, B.M., AlGhadhban, A., Allal, A.: An efficient bearing fault detection strategy based on a hybrid machine learning technique. Sci. Rep. 15(1), 18739 (2025)

[9] Bharatheedasan, K., Maity, T., Kumaraswamidhas, L.A., Durairaj, M.: Enhanced fault diagnosis and remaining useful life prediction of rolling bearings using a hybrid multilayer perceptron and LSTM network model. Alexandria Eng. J. 115, 355–369 (2025)

[10] Borandag, E.: Software fault prediction using an RNN-based deep learning approach and ensemble machine learning techniques. Appl. Sci. 13(3), 1639 (2023)

[11] Alkhanafseh, Y., Akinci, T.C., Ayaz, E., Martinez-Morales, A.A.: Advanced dual RNN architecture for electrical motor fault classification. IEEE Access 12, 2965–2976 (2023)

[12] Seba, A.M., Gemeda, K.A., Ramulu, P.J.: Prediction and classification of IoT sensor faults using hybrid deep learning model. Discov. Appl. Sci. 6(1), 9 (2024)

[13] Alhanaf, A.S., Farsadi, M., Balik, H.H.: Fault detection and classification in ring power system with DG penetration using hybrid CNN-LSTM. IEEE Access 12, 59953–59975 (2024)

[14] Alsumaidaee, Y.A.M., Paw, J.K.S., Yaw, C.T., Tiong, S.K., Chen, C.P., Yusaf, T., Abdalla, A.N.: Fault detection for medium voltage switchgear using a deep learning hybrid 1-D-CNN-LSTM model. IEEE Access 11, 97574–97589 (2023)

[15] Zabin, M., Choi, H.-J., Uddin, J.: Hybrid deep transfer learning architecture for industrial fault diagnosis using Hilbert transform and DCNN–LSTM. J. Supercomput. 79(5), 5181–5200 (2023)

[16] Wu, Y., Ma, X.: A hybrid LSTM-KLD approach to condition monitoring of operational wind turbines. Renew. Energy 181, 554–566 (2022)

[17] Venkatasubramanian, S., Raja, S., Sumanth, V., Dwivedi, J.N., Sathiaparkavi, J., Modak, S., Kejela, M.L.: Fault diagnosis using data fusion with ensemble deep learning technique in IIoT. Math. Probl. Eng. 2022(1), 1682874 (2022)

[18] Fallah, D., Abdul-Kareem, B.J., Murad, N.M., Mahdi, A.F., Janan, O., Maidin, S.S.: Predictive data analytics for fault diagnosis and energy optimization in industrial IoT environments. Int. J. Eng. Sci. Inf. Technol. 5, 532–541 (2025). https://doi.org/10.52088/ijesty.v5i2.1392

[19] Fault prediction in tablet press equipment. Kaggle. https://www.kaggle.com/datasets/thegoanpanda/fault-prediction-in-tablet-press equipmen