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Research Paper

Scalable Defective Tool Recognition and Classification System for Industry 4.0 Manufacturing Workshops

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ABSTRACT

In recent years, industrial automation and smart manufacturing have witnessed rapid growth, with global reports indicating that over 65% of workshops now rely on visual inspection systems to improve productivity and reduce operational errors, yet manual tool identification still contributes to nearly 30% of workflow inefficiencies and misclassification-related downtime. In this context, this work focuses on the automated recognition of industrial tools in workshop environments using intelligent vision-based techniques. The problem addressed in this study is the inaccuracy, time consumption, and subjectivity associated with traditional manual tool identification systems, where human operators rely on visual inspection and experience to classify tools. The research presents an intelligent image classification system that leverages deep learning and machine learning techniques for robust tool identification. The system utilizes InceptionResNetV2 (Inception Residual Network Version 2) as a pre-trained Convolutional Neural Network (CNN) for extracting high-level visual features from input images through transfer learning. These extracted feature vectors are then used to train multiple classifiers, including Decision Tree Classifier (DTC), K-Nearest Neighbors (KNN), and Perceptron Classifier (PC) as baseline models. The proposed approach introduces a hybrid ensemble model that combines a Deep Neural Network (DNN) for probability-based feature transformation with a Random Forest Classifier (RF) for final classification, forming a stacked learning architecture that enhances prediction accuracy and generalization. The system incorporates comprehensive evaluation metrics such as accuracy, precision, recall, F1-score, confusion matrix, and Receiver Operating Characteristic (ROC) curve with Area Under Curve (AUC) analysis to validate performance across multi-class industrial tool datasets. Additionally, a user-friendly Graphical User Interface (GUI) developed using Tkinter, along with role-based authentication via a MySQL database, enables seamless interaction for both administrators and end users. Experimental results demonstrate that the proposed hybrid model significantly outperforms traditional classifiers by effectively capturing complex patterns in tool images, thereby providing a scalable, efficient, and accurate solution for automated industrial tool recognition in real-world workshop environments.

Keywords: Industrial automation, Tool identification, Visual inspection systems, Computer numerical control, Programmable logic control

1. INTRODUCTION

In modern industrial settings, the need for smart and automated systems has become paramount, especially in workshops where accurate identification and usage of tools are critical for safety, efficiency, and productivity. The proposed project, titled "Ensemble Feature Learning for Accurate Recognition of Industrial Tools in Workshop Environments," aims to design an intelligent system that automates the process of recognizing various industrial tools through advanced image-based learning techniques. By leveraging ensemble feature learning methods combining CNN with classical classifiers like SVM, KNN, and Random Forest, the system ensures high accuracy even under challenging conditions such as cluttered backgrounds or partial occlusions. This solution finds significant applications in smart manufacturing systems for automated tool recognition and inventory management**,** industrial robotics for precise tool selection and manipulation, training simulators to help newcomers identify tools effectively, maintenance systems to monitor tool usage and replacement schedules, and safety-critical environments where incorrect tool usage can lead to hazardous consequences. The system enhances reliability, reduces human error, and plays a vital role in shaping the future of Industry 4.0 automation solutions as shown in fig 1.

Fig 1. Industrial tools recognition

Over the past 10 years, different technologies have boosted data-acquisition, communications, and processing capabilities. This strong development has led to the inauguration of a new concept: the Internet of Things (IoT). Although this concept might have direct applications in the daily life of the public, its successful implementation in industrial environments seems to be a more complex issue, as recent reviews have outlined [1]. This is the case of machining workshops, where many factors limit the range of IoT solutions. First, the integration of new sensors in existing machines is not easy, as durable machine-tools are usually designed for a long life and most existing machines were built before the development of the IoT or the Industry 4.0 paradigms [2]. Therefore, communication capabilities and integrated sensors built into machine-tools are very limited. In those cases, the only way to extract information from them would be through the machine's CNC (Computer Numerical Control). However, the CNC is not often available, given that its primary function is to control the machine-tool. Therefore, the most common solution is to access the PLC (Programmable Logic Controller) of the machine. Reading the PLC parameters is one way of extracting many parametric values from the CNC. This solution has been widely used during the last decade; i.e., for developing adaptive remote controllers for milling machines through an internet connection [3]. The first element for suitable IoT solutions in small workshops should therefore be a Data Acquisition Platform (DAP) connected to the PLC of the machine. The first DAP for manufacturing tasks was demonstrated over 20 years ago [4] for tool condition monitoring. However, the opportunity of setting up a real implementation was never demonstrated, due mainly to the very limited access to commercial CNCs at that time. To overcome this limitation, open architecture CNCs, once very rare in industrial workshops, were used in most studies over the past twenty years. In very recent years, some studies have described the new communication capabilities incorporated in commercial CNCs. Having established reliable solutions for data communication, the research focus moved on towards the definition of the best Key Performance Indicators extracted from the IoT platforms for manufacturing optimization.

However, the data-acquisition stage is, however, not the only challenge for machine-workshop IoT solutions. Data processing and analysis are also subject to very restricted conditions and data features. As will be explained, the analysis of workshop machining processes will often have to contend with incomplete and unbalanced datasets. Besides, the data will have too many inputs, lessening its reliability. It will therefore be necessary to reduce the number of inputs and to eliminate repeated instances without losing information. Machine-learning techniques have many capabilities that are especially suitable to overcome these limitations. First, they generalize models to new conditions, thereby reducing the number of expensive experimental tests to be performed. Second, machine-learning techniques can extract useful information for unbalanced datasets. Third, machine-learning techniques reduce the number of features without losing information. Fourth, machine-learning techniques are able to complete missing attributes, due to sensor malfunctions and data-transmission errors. Nevertheless, the studies on machine-learning algorithm applications to predict machining-process performance have been demonstrated in laboratory datasets. Datasets generated under laboratory conditions have some extremely different features to those generated in real workshops. Under laboratory conditions, a very small number of inputs are varied from one experiment to the next, there is almost no experimental repetition, the experimental conditions are carefully selected, mainly by factorial or Taguchi experimental design, and all inputs and outputs are carefully measured, and validated before the next experiment is performed, as outlined by the most exemplary reviews [5].

In modern industrial workshops, the accurate identification of tools is critical for automating processes, ensuring worker safety, reducing downtime, and optimizing inventory. However, traditional manual tool recognition systems are error-prone, time-consuming, and inefficient in dynamic and cluttered workshop environments. The challenge lies in building an intelligent system that can effectively recognize and classify a diverse range of tools under varying lighting conditions, orientations, occlusions, and image quality. Current single-algorithm systems either lack the depth of learning (in traditional ML models) or fail to generalize effectively when relying solely on deep learning.

2. LITERATURE SURVEY

2.1 Ensemble Learning in Deep Learning-Based Recognition Systems

Ensemble learning has been widely adopted to improve model generalization and classification performance across various domains. Alshazly *et al.* [6] proposed an ensemble framework based on deep Convolutional Neural Networks (CNNs), particularly Visual Geometry Group (VGG)-like architectures, for ear recognition. Their approach involved training multiple models with varying depths, leveraging both randomly initialized and pre-trained networks, and combining them into an ensemble to enhance feature discrimination. The system demonstrated robust performance across multiple datasets, including AMI, AMIC, and WPUT, under both controlled and uncontrolled conditions.

Similarly, de Zarzà *et al.* [7] explored advanced ensemble strategies such as bagging, stacking, and cascading neural networks for healthcare prediction tasks. Their cascading ensemble approach utilized a two-layer architecture, where predictions from initial models were fed into subsequent models for refinement. The integration of ensemble voting further improved performance, achieving a notable accuracy of 91.5% in diabetes prediction, highlighting the effectiveness of hierarchical ensemble learning.

2.2 Ensemble Techniques for Sensor-Based and Activity Recognition Systems

Ensemble methods have also been extensively applied in human activity recognition (HAR) using sensor data. Ku Abd. Rahim *et al.* [8] proposed an ensemble-based classification system for recognizing daily human activities using smartphone inertial sensors. Their methodology incorporated multiple ensemble techniques, including Bagging, AdaBoost, Rotation Forest, Ensembles of Nested Dichotomies (END), and Random Subspace, with Support Vector Machine (SVM) and Random Forest (RF) as base learners. The system demonstrated strong performance using both holdout and 10-fold cross-validation strategies.

Haider *et al.* [11] evaluated machine learning models for activity recognition using the CogAge dataset, which integrates data from multiple wearable devices. Their approach achieved high classification accuracy, with Random Forest and SVM reaching 96.61% and 94.1%, respectively.

Saha *et al.* [12] further addressed challenges such as device variability and placement differences in smartphone-based activity recognition. They proposed an ensemble of condition-based classifiers capable of adapting to varying sensor configurations, thereby improving robustness and generalization.

Bhattacharya *et al.* [14] introduced a deep ensemble model termed *Ensem-HAR*, combining multiple architectures such as CNN, CNN-LSTM, ConvLSTM, and Stacked LSTM. The model employed stacking with a meta-learner to generate final predictions and achieved high accuracy across benchmark datasets, demonstrating the effectiveness of deep ensemble learning for time-series data.

2.3 Ensemble Learning in Cybersecurity and IoT Systems

In the domain of cybersecurity, ensemble learning has been utilized to enhance intrusion detection systems (IDS). Alalwany *et al.* [9] proposed a stacking-based ensemble IDS that integrates machine learning and deep learning models within a Kappa Architecture framework for real-time Internet of Medical Things (IoMT) data processing. The system achieved high detection accuracy for both binary and multi-class classification tasks, demonstrating its effectiveness in identifying various cyberattacks.

Alkadi *et al.* [10] introduced *RobEns*, a robust ensemble framework designed to improve the resilience of IDS models against adversarial machine learning (AML) attacks. Their study evaluated multiple ML-based IDS models under black-box attack scenarios and proposed defense strategies such as feature squeezing and adversarial training. The results highlighted both the vulnerabilities and robustness improvements achievable through ensemble-based defenses.

2.4 Hybrid and Deep Learning Models for Time-Series and Signal Analysis

Hybrid deep learning architectures combining CNNs and recurrent models have shown significant promise in handling time-series and signal data. Przybyś-Małaczek *et al.* [13] investigated tool state recognition in industrial milling processes using LSTM, SVM, and boosting ensemble decision trees.

Their work emphasized the importance of feature selection and preprocessing for improving classification accuracy in industrial applications.

Lee *et al.* [15] proposed a multi-stage fault diagnosis system that integrates a Convolutional Triplet Network for feature extraction with an ensemble classifier for fault detection. Their approach effectively captured both spatial and temporal features from vibration signals, outperforming traditional single-stage models in detecting machinery faults.

3. PROPOSED METHODOLOGY

The proposed methodology presents a structured and intelligent framework for automated industrial tool recognition using image-based learning techniques. The study follows a sequential pipeline that begins with dataset acquisition and preprocessing, proceeds through deep feature extraction and multi-model learning, and concludes with robust classification and real-time prediction. The approach integrates transfer learning with classical machine learning and hybrid ensemble strategies to improve classification accuracy and reliability under complex workshop conditions. Feature persistence and model storage mechanisms are incorporated to reduce redundant computation, while a graphical user interface enables seamless interaction for both administrative and user-level operations. The methodology emphasizes adaptability, efficiency, and scalability, ensuring consistent performance across varying tool categories and imaging conditions as shown in fig 2.

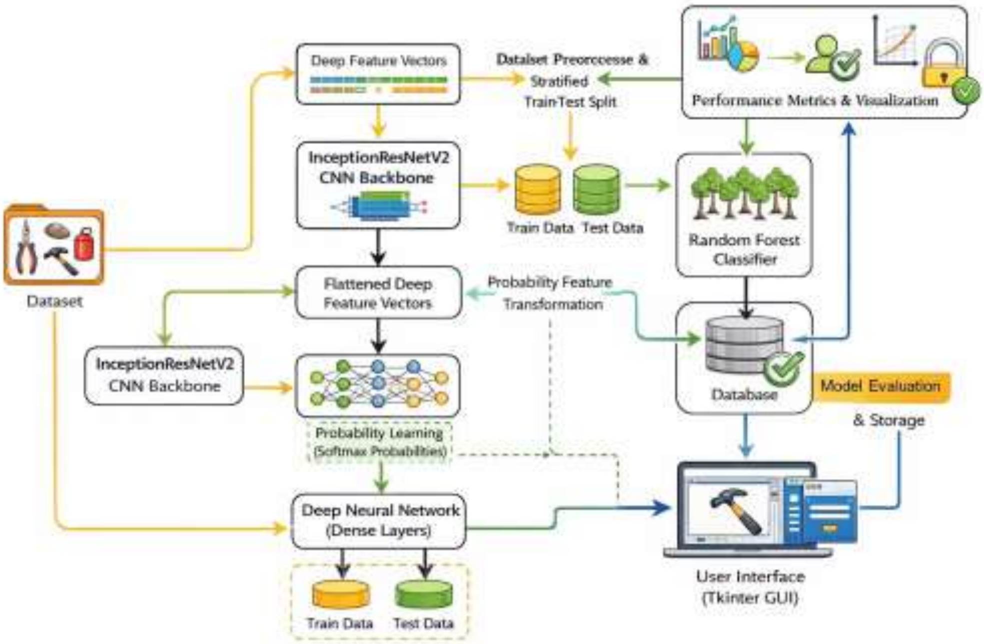

Fig. 2. Proposed system architecture for industrial tools.

The system provides a desktop-based graphical user interface developed using the Tkinter framework, enabling intuitive interaction between users and the backend models. The interface supports role-based access, distinguishing between administrative and general user operations. Administrators can upload datasets, extract features, split data, train models, and evaluate performance, while users are allowed to perform image-based predictions. All user actions are internally mapped to backend processing functions, ensuring smooth coordination between interface and computation. User authentication and role management are handled through a MySQL database, which stores user credentials and access roles. Signup and login functionalities verify user details through secure database queries, ensuring controlled access to system functionalities. Based on the authenticated role, the interface dynamically enables or restricts available operations. This mechanism ensures data integrity, security, and proper separation of administrative and user-level tasks. The input dataset consists of industrial tool images organized into class-specific directories, where each folder represents a unique tool category. The dataset upload mechanism dynamically reads folder names to generate class labels automatically. This structured organization simplifies label assignment and ensures consistency during training and evaluation. Supported image formats are validated before further processing to avoid invalid inputs. Before feature extraction, all images are resized to a fixed resolution of 128×128 pixels to maintain uniformity across samples. Pixel values are normalized to improve numerical stability and learning efficiency. This preprocessing step reduces computational complexity while preserving essential visual characteristics. The standardized images are then forwarded to the deep feature extraction stage.

A pre-trained InceptionResNetV2 model is employed to extract high-level and discriminative visual features from tool images. The classification layers of the network are removed, and global average pooling is used to obtain compact feature vectors. By leveraging transfer learning, the system avoids training a deep model from scratch while benefiting from rich visual representations. The extracted features form the foundation for all subsequent classification tasks. To enhance efficiency, the extracted feature vectors and corresponding labels are stored locally using compressed file formats. Class names are saved in a JSON file to ensure consistent label mapping during training and prediction. This persistent storage mechanism prevents redundant feature extraction in future runs. As a result, model training and evaluation become significantly faster and more resource-efficient. The processed feature dataset is divided into training and testing subsets using a stratified splitting strategy. This ensures that class distributions are preserved across both sets, preventing bias during evaluation. Typically, 80% of the data is used for training and 20% for testing. This step establishes a reliable foundation for fair model comparison and performance assessment. Baseline classification is performed using traditional machine learning models, namely the Decision Tree Classifier and the Perceptron Classifier. These models operate directly on the flattened deep feature vectors extracted from the convolutional network. Their inclusion provides a benchmark for evaluating the effectiveness of more advanced approaches. Performance metrics obtained from these models highlight the limitations of single-classifier systems. The proposed hybrid model combines a Deep Neural Network and a Random Forest classifier to enhance prediction accuracy and robustness. The Deep Neural Network learns complex non-linear feature relationships and generates class probability distributions. These probability vectors are then passed to a Random Forest classifier, which performs the final decision-making. This ensemble strategy reduces overfitting and improves generalization under challenging visual conditions. Model performance is evaluated using multiple statistical metrics, including accuracy, precision, recall, F1-score, sensitivity, and specificity. Confusion matrices and ROC–AUC curves provide deeper insight into class-wise prediction behavior. Visualizations such as heatmaps and ROC plots assist in interpreting model strengths and weaknesses. This comprehensive evaluation ensures reliable and objective performance assessment.

For unseen images, the same preprocessing and feature extraction pipeline is applied to maintain consistency. The trained hybrid model predicts the corresponding tool category based on learned patterns. Prediction results are displayed through the interface and visually annotated on the input image. This real-time feedback enables practical usability in workshop environments. All trained models are saved using appropriate persistence techniques to allow reuse without retraining. The system supports retraining when updated datasets are provided, ensuring adaptability to new tools or variations. Stored models and features enable rapid deployment and continuous improvement. This capability ensures long-term usability and scalability of the research framework.

3.2 Feature extraction

InceptionResNetV2 is a deep convolutional neural network that combines the strengths of Inception modules (multi-scale feature extraction) and Residual connections (skip connections for stable deep learning). In the research it is used as a pre-trained feature extractor (transfer learning) where images are passed through the network (without training it further) to generate rich, high-level feature vectors. These extracted features represent complex patterns of industrial tools (shape, edges, texture), which are then used by machine learning models for accurate classification as shown in fig 3.

The input image is resized to 128×128×3 and normalized (pixel values scaled between 0 and 1). This ensures uniform input format and helps the network process images efficiently without bias due to scale differences. The image first passes through basic convolution and pooling layers, where low-level features like edges, corners, and textures are extracted. These layers act as the foundation for understanding visual patterns in the image.

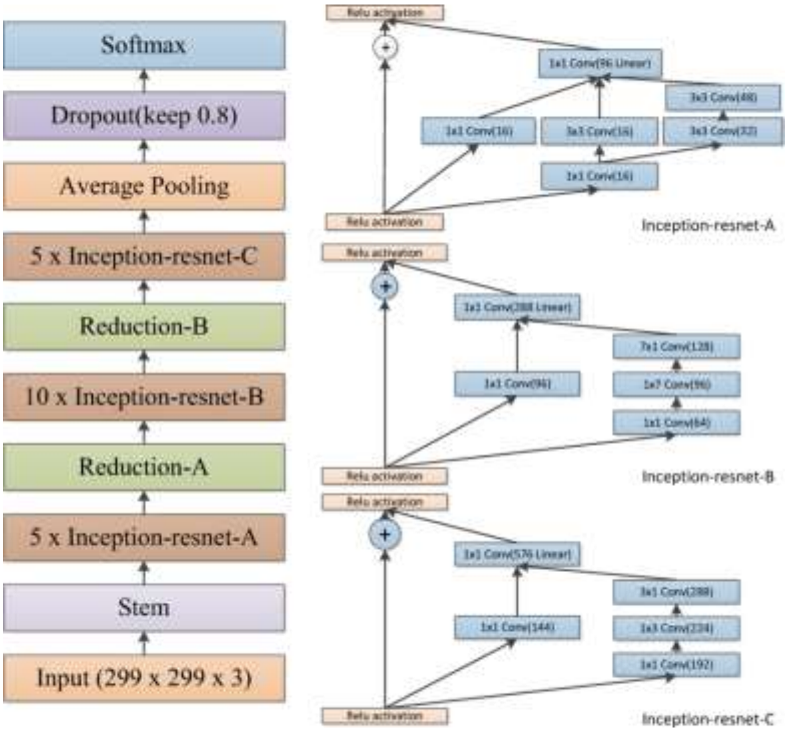

Fig 3. Generalized layered architecture of InceptionResnetv2 model

Inception blocks apply multiple convolution filters (1×1, 3×3, 5×5) in parallel on the same input. This allows the network to capture features at different scales, such as small details (edges) and larger structures (tool shapes), improving feature richness. Residual connections directly pass input features to deeper layers, bypassing intermediate layers. This helps avoid vanishing gradient problems and allows the network to learn deeper representations without losing important information. Multiple Inception-ResNet blocks are stacked together, enabling the model to learn hierarchical features—from simple edges to complex object structures like handles, blades, or tool contours. Instead of fully connected layers, the model uses Global Average Pooling, which converts feature maps into a compact feature vector. This reduces overfitting and produces a fixed-length representation for each image. The final output is a high-dimensional feature vector, which captures the most important visual characteristics of the image. In your project, this vector is used as input for classifiers like DT, KNN, and the Hybrid model.

4. RESULT ANALYSIS

Fig 4 illustrates the Admin interface after successful login and dataset upload in the proposed industrial tool recognition system. Upon selecting the dataset directory, the system automatically loads the images, detects the class folders, and displays confirmation details in the output panel, including the message *"Dataset loaded successfully"*, the total number of classes (4), and the identified tool categories such as *Gasoline Can, Hammer, Pliers*, and *Pebble*. The interface also presents clearly labeled action buttons for subsequent stages—feature extraction using InceptionResNetV2, dataset splitting, training of Decision Tree, KNN, Perceptron, and Hybrid classifiers such as allowing the Admin to seamlessly proceed with model training and evaluation. This screen confirms correct dataset ingestion and serves as the starting point for the complete learning pipeline.

```
Dataset loaded successfully
Total classes: 4
Classes: ['Gasoline Can', 'Hammer', 'Pliers', 'pebbel']
```

Fig 4. Uploading dataset interface after admin login/signup

Fig 5. shows the successful completion of feature extraction using the InceptionResNetV2 model after Admin interaction. Once the dataset is selected, the system either extracts deep visual features from all images using the pre-trained InceptionResNetV2 network or directly loads previously saved feature vectors from the model folder to avoid redundant computation. The confirmation message *"Loaded features from model folder"* indicates that the CNN-based feature embeddings have been correctly generated and stored, making them ready for dataset splitting and subsequent classifier training. This step transforms raw industrial tool images into compact, high-level feature representations that form the foundation for accurate classification by both existing and hybrid learning models.

Loaded features from model folder

Fig 5. InceptionResNetV2 feature extraction completed.

Fig 5 shows confusion matrix and multi-class ROC curves demonstrate the superior performance of the proposed Hybrid DNN with Random Forest (DNN Probs → RF) model for industrial tool recognition. The confusion matrix shows highly accurate classification across all tool categories, with near-perfect recognition for *Gasoline Can* and *Pliers* and minimal misclassification among visually similar classes, indicating strong decision refinement by the ensemble model. The ROC analysis further confirms this robustness, achieving an AUC of 1.00 for Gasoline Can, 0.97 for Pebble, 0.96 for Pliers, and 0.93 for Hammer, reflecting excellent class separability. These results validate that combining DNN-learned probability representations with Random Forest ensemble learning significantly enhances discrimination capability and overall classification accuracy compared to individual classifiers, making the proposed hybrid approach well-suited for complex workshop environments.

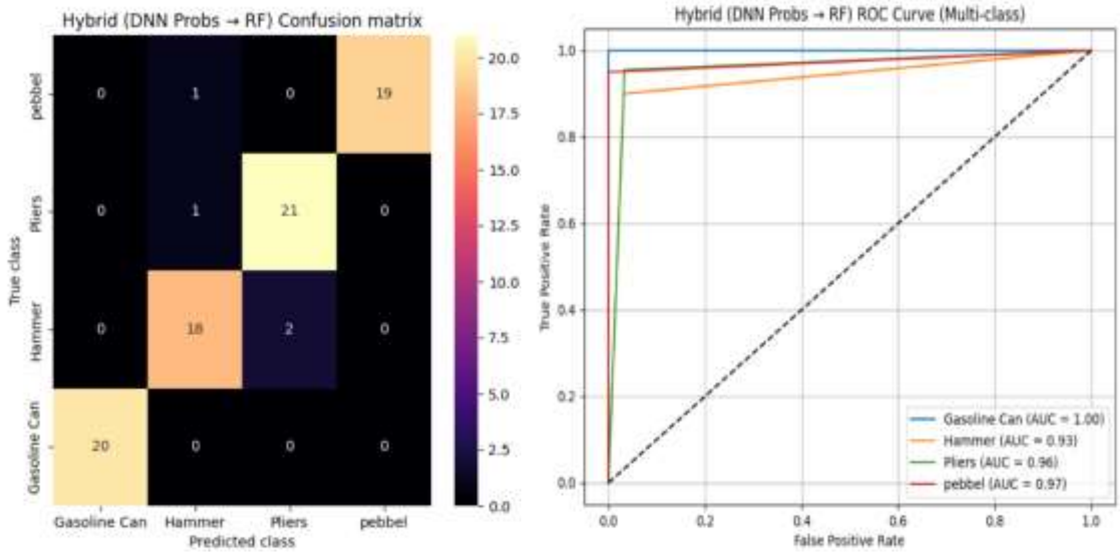

Fig 6. Confusion matrix and ROC Curve obtained using Hybrid DNN with RF classifier

Table 1 presents a comprehensive performance comparison of the KNN, Decision Tree Classifier (DTC), Perceptron, and the proposed Hybrid DNN with Random Forest models for industrial tool recognition using CNN-extracted features. Among the conventional classifiers, KNN demonstrates strong performance with an accuracy of 90.68%, indicating its effectiveness in leveraging distance-based learning on discriminative deep features, while the Perceptron achieves a comparable accuracy of 89.02%, reflecting reasonable linear separability of the feature space. In contrast, the Decision Tree Classifier records the lowest performance, with an accuracy of 73.17%, highlighting its limited generalization capability and sensitivity to feature variability in complex workshop environments. Notably, the proposed Hybrid DNN with RF model outperforms all baseline approaches, achieving the highest accuracy (95.12%), precision (95.32%), recall (95.11%), and F-score (95.19%), which confirms its superior ability to capture complex feature relationships and refine class decisions through ensemble learning. These results clearly demonstrate that integrating DNN-based probability learning with Random Forest classification significantly enhances robustness and recognition accuracy compared to individual machine learning models.

Table 1: Performance comparison for the KNN, DTC, perceptron and Hybrid DNN with RF

Algorithms Name	Accuracy	Precision	Recall	F-score
KNN	90.68%	91.90%	91.72%	91.73%
DTC	73.17%	74.22%	73.18%	73.51%
Perceptron	89.02%	90.49%	89.31%	89.26%
Hybrid DNN with RF	95.12%	95.32%	95.11%	95.19%

Fig 7. Prediction on test data using hybrid DNN with RF model

Fig 7 illustrates the prediction results on unseen test images using the proposed Hybrid DNN with Random Forest model. The model successfully identifies and labels the industrial tools by overlaying the predicted class names directly on the input images, demonstrating its practical applicability. In the first example, the system accurately recognizes the tool as Pliers, while in the second case, it correctly classifies the image as a Hammer, indicating strong generalization capability on diverse visual inputs. These results confirm that the hybrid approach effectively leverages deep CNN features and ensemble decision refinement to deliver reliable and accurate tool recognition in real-world workshop environments.

5. CONCLUSION

The research successfully presents an ensemble feature learning framework for accurate recognition of industrial tools in workshop environments, integrating deep learning and classical machine learning techniques into a unified system. A pre-trained InceptionResNetV2 model is effectively utilized for robust feature extraction, transforming raw tool images into highly discriminative representations that capture complex visual patterns. Multiple baseline classifiers, including DTC, KNN, and Perceptron, are implemented to establish comparative performance benchmarks, revealing the limitations of standalone models in handling inter-class similarity and environmental variability. To overcome these challenges, a proposed Hybrid DNN with RF model is developed, where a DNN learns class probability distributions and a Random Forest refines final decisions through ensemble learning. Extensive experimental evaluation using confusion matrices, ROC–AUC curves, and statistical performance metrics demonstrates that the hybrid approach consistently outperforms existing methods, achieving superior accuracy, precision, recall, and F-score. The system is further strengthened by a Tkinter-based GUI and role-based authentication, enabling secure dataset management, model training, and real-time prediction. The results validate that combining deep CNN features with probabilistic and ensemble learning significantly enhances robustness, generalization, and reliability, making the proposed framework highly suitable for intelligent automation and safety-oriented applications in industrial workshop environments.

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