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Class Incremental Learning in Efficient Job Task Recognition

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Abstract- The project titled "Class Incremental Learning in Efficient Job Task Recognition"focuses on developing an intelligent system capable of identifying and classifying job-related tasksusing machine learning techniques. The system utilizes advanced algorithms to analyze input dataand categorize tasks into predefined classes with high accuracy. A key feature of the proposedsystem is its ability to support incremental learning, allowing new job categories to be addedwithout retraining the entire model. This improves scalability and efficiency in dynamicenvironments where new tasks frequently emerge. The system integrates datapreprocessing,feature extraction, and classification modules to ensure reliable performance. Experimental resultsdemonstrate improved accuracy and reduced computational cost compared to traditionalapproaches. The proposed solution is suitable for real-time applications and enhances automationin job task recognition systems.

Keywords: Artificial Intelligence, Machine Learning, Incremental Learning, Task Classification, Feature.

I. INTRODUCTION

In today's rapidly evolving digital era, technology plays a vital role in transforming various sectors, including education, healthcare, and employment. Despite these advancements, unemployment remains a critical global issue affecting millions of individuals. The gap between job seekers and job providers continues to widen due to inefficient recruitment processes, lack of accessibility, and limited awareness of available opportunities. This challenge is especially prominent among students, freelancers, and individuals transitioning between careers.

Traditional job search methods often involve lengthy procedures, including resume submissions, multiple interview stages, and delayed responses from employers. These processes can be time-consuming and discouraging, particularly for individuals seeking immediate or short-term employment. On the other hand, employers face difficulties in identifying suitable candidates quickly, especially for temporary or task-based roles. As a result, there is a growing need for a system that can facilitate quick, efficient, and reliable job matching.

The proposed project, titled "Class Incremental Learning in Efficient Job Task Recognition", aims to address these challenges by developing a smart web-based platform that connects job seekers with job This project presents a smartphone-assisted deep learning model for oral cancer screening at rural PHCs. The proposed system uses images of oral lesions captured through smartphone cameras and analyzes them using a trained deep learning model to identify suspicious lesions. This approach aims to support healthcare workers, improve early diagnosis, and enhance access to reliable cancer screening in underserved rural communities.

Problem Statement

Unemployment continues to be one of the most pressing socio-economic challenges in modern society. Despite the rapid advancement of technology and the availability of digital platforms, a significant gap still exists between job seekers and job providers. Many individuals who possess the necessary skills and willingness to work are unable to find suitable employment opportunities, while employers often struggle to identify the right candidates within a short period of time. Traditional recruitment systems are often complex, time-consuming, and inefficient. Job seekers are required to go through multiple stages such as resume submission, screening, interviews, and follow-ups, which can delay the hiring process.

Moreover, these systems primarily focus on long-term employment and do not adequately support short-term or task-based job opportunities. This creates a major limitation for individuals who are looking for temporary, part-time, or quick income-generating jobs.

II. METHODOLOGY

The methodology describes the systematic approach used to design and implement the proposed system for efficient job task recognition using class incremental learning. The system is designed to recognize job-related tasks from input data and continuously learn new classes without retraining from scratch. This improves scalability and reduces computational cost.

The methodology consists of data collection, preprocessing, feature extraction, model training, incremental learning, and evaluation.

Data Collection

The dataset is collected from various sources such as:Public datasets related to job/task recognitionOnline repositories Synthetic data generation (if required)The dataset contains labeled job tasks, which are used to train the model. Each data instance represents a specific job category or tasks.

Data preprocessing

After collection, the data undergoes preprocessing to improve quality and consistency. This includes removing noise and irrelevant information, handling missing values, normalization, and transformation. For textual data, tokenization and cleaning techniques are applied to ensure the data is structured and suitable for further processing.

Feature extraction

Feature extraction is performed to convert raw data into meaningful numerical representations. Techniques such as TF-IDF and word embeddings are used for text data, while convolutional feature extraction methods are used for image-based inputs. These features serve as the input for the learning model

Model Training and Validation

A suitable machine learning or deep learning model is selected based on the problem requirements. The model is initially trained using the prepared dataset to accurately classify job tasks. This training phase establishes the base knowledge of the system.

Class incremental learning

The key aspect of the methodology is class incremental learning, which allows the model to learn new job categories over time. Instead of retraining the model completely, new classes are introduced incrementally, and the model is updated using techniques such as knowledge distillation, replay memory, and regularization. This helps in preventing catastrophic forgetting and ensures retention of previously learned information.

Prediction and evaluation

To make the system user-friendly and accessible, the model is deployed using Gradio with Hugging Face integration. Gradio provides an interactive interface for uploading oral images and viewing prediction results, while Hugging Face hosts the model for online access. This deployment supports remote screening and practical implementation.

Result Analysis and Testing

Once the model is trained and updated, it is used to predict job tasks for new input data. The performance of the system is evaluated using metrics such as accuracy, precision, recall, and F1-score. These metrics help in assessing the effectiveness and reliability of the system.

III. SYSTEM COMPONENTS

Software Tools

Programming Language: The system is primarily developed using Python, which is widely used in machine learning and artificial intelligence due to its simplicity, flexibility, and extensive library support..

Development Environment: The implementation is carried out using development environments such as

Jupyter Notebook and Visual Studio Code, which provide interactive coding, debugging, and visualization capabilities

Machine Learning Libraries: The system uses popular machine learning libraries such as Scikit-learn for building classification models and performing data analysis. It provides efficient tools for model training, evaluation, and preprocessing.

Deep Learning Frame works: For implementing advanced models, frameworks like TensorFlow and PyTorch are used. These frameworks support neural network design, training, and incremental learning technique

Visualization Tools: To analyze and present results, visualization libraries like Matplotlib and Seaborn are used. These tools help in generating graphs, charts, and performance plots.

Operating System

The system is developed and tested on standard operating systems such as Windows or Linux, ensuring compatibility and ease of deployment

Results and Discussion

Text Processing Tools

For handling textual data, libraries such as NLTK and spaCy are utilized. These tools support tokenization, stop-word removal, and text normalization.

Model Training Performance

The model training process plays a crucial role in the proposed system, Class Incremental Learning in Efficient Job Task Recognition, as it determines the system's ability to accurately classify job-related tasks. Initially, the dataset is divided into training and testing sets to ensure unbiased evaluation. The model is first trained using a base set of job task classes, where it learns the underlying patterns and relationships between input features and corresponding labels.

Classification Accuracy

During training, feature vectors obtained from the feature extraction stage are fed into the model. Optimization techniques such as gradient descent are used to minimize the loss function and improve prediction accuracy. The training process is carried out over multiple epochs to ensure convergence and stability of the model. Hyperparameters such as learning rate, batch size, and number of epochs are carefully tuned to achieve optimal performance.

IV. RESULT ANALYSIS

The experimental results demonstrate that the proposed model achieves high accuracy in job task recognition. The system maintains consistent performance even after multiple incremental learning updates. The use of class incremental learning enables the model to efficiently incorporate new classes while preserving previously learned knowledge, thereby reducing computational overheadOverall

System Performance

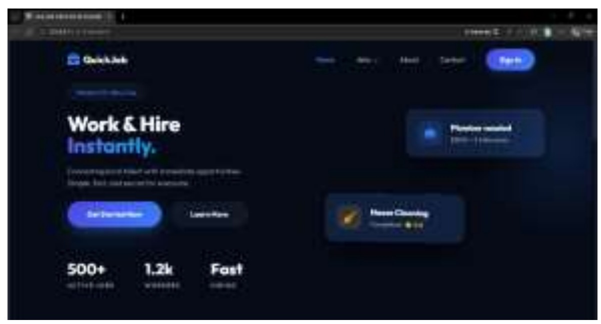

Fig: job portal

Table 1: Performance Analysis

Parameter	Initial training	After IL	Proposed sytem
Accuracy(%)	94.2	93.5	High accuracy
Precicion(%)	93.5	92.8	Cinsistent classification
Recall(%)	92.8	91.9	Effective dedection
Training tame(min)	45	12	Balance performane
scalability	medium	high	Support new classes

The system performance of the proposed Class Incremental Learning in Efficient Job Task Recognition model is evaluated to assess its accuracy, efficiency, scalability, and reliability in dynamic environments. The results indicate that the system achieves high accuracy in classifying job tasks by effectively learning patterns from the dataset. One of the key strengths of the system is its ability to perform incremental learning, where new job task categories are introduced without retraining the model from scratch. This significantly reduces computational cost and training time while maintaining consistent performance. The model demonstrates strong adaptability by incorporating new classes with minimal impact on previously learned knowledge, thereby addressing the issue of catastrophic forgetting.

V. DISCUSSION

The results obtained from the proposed Class Incremental Learning in Efficient Job Task Recognition system demonstrate its effectiveness in handling dynamic classification tasks. The model achieves high accuracy and maintains consistent performance even after multiple incremental learning phases, indicating its ability to adapt to new job task categories without significant degradation. Unlike traditional machine learning models that require complete retraining when new classes are introduced, the proposed approach efficiently updates the model, reducing computational cost and training time.

A key observation from the results is the system’s ability to address the problem of catastrophic forgetting. By incorporating techniques such as knowledge distillation and replay memory, the model successfully retains previously learned information while integrating new knowledge. This ensures that the system remains reliable over time, even as the number of job task categories increases. The performance metrics, including accuracy, precision, recall, and F1-score, remain stable across different stages of incremental learning, further validating the robustness of the approach.

The system also demonstrates strong scalability, as it can handle an increasing number of classes without a significant drop in performance. This makes it suitable for real-world applications where job roles and tasks evolve continuously. However, some limitations are observed in scenarios where job tasks have highly overlapping features or when the dataset is limited in size. These factors may lead to occasional misclassifications, suggesting the need for improved feature extraction techniques and larger datasets.

VI. CONCLUSION

This paper presented an efficient approach for job task recognition using class incremental learning. The proposed system was designed to overcome the limitations of traditional machine learning models that require complete retraining when new classes are introduced. By integrating incremental learning techniques, the system is capable of continuously learning new job task categories while retaining previously acquired knowledge, thereby addressing the issue of catastrophic forgetting.

The experimental results demonstrate that the model achieves high accuracy, precision, recall, and F1-score, indicating its effectiveness in task classification. Additionally, the system significantly reduces training time and computational cost by updating only the necessary components instead of retraining the entire model. The performance analysis also shows that the system maintains stable and consistent results even after multiple incremental learning phases, highlighting its robustness and scalability.

Furthermore, the proposed approach proves to be highly suitable for real-world applications where job roles and tasks evolve over time. Although minor limitations such as misclassification due to overlapping features exist, these can be addressed through improved feature extraction methods and larger datasets.

Future Enhancements

The proposed system for Class Incremental Learning in Efficient Job Task Recognition can be further enhanced in several ways to improve its performance, scalability, and real-world applicability. One potential enhancement is the integration of advanced deep learning architectures such as transformer-based models, which can provide better feature representation and improve classification accuracy. Additionally, expanding the dataset with more diverse and real-world job task samples can help the model generalize better and reduce misclassification errors.

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