Multi-Label Image Classification For Online Educational Platforms Using SGD

[1]Mahammad Javid,[2]Dr.Nelli Chandrakala

[1]M. Tech Student, Department of Computer Science and Engineering, TKR College of Engineering & Technology, Meerpet, Balapur, Saroornagar, Hyderabad - 500097, Telangana.

[1]Email : mdjavid024@gmail.com

[2]Associate Professor, Department of Computer Science and Engineering, TKR College of Engineering & Technology, Meerpet, Balapur, Saroornagar, Hyderabad - 500097, Telangana.

[2]Email : Chandrakala@tkrcet.com

ABSTRACT

The rapid growth of online educational platforms has led to an increasing volume of visual learning content, necessitating effective image classification methods to improve content organization and accessibility. Unlike traditional single-label classification, educational images often belong to multiple categories simultaneously, such as subject areas, concepts, and instructional contexts, which makes multi-label classification essential. This study proposes a robust multi-label image classification framework tailored for online educational platforms, leveraging convolutional neural networks (CNNs) trained with Stochastic Gradient Descent (SGD) optimization. Our approach employs a deep CNN backbone model adapted for multi-label tasks by utilizing sigmoid activation functions on the output layer to predict the presence of multiple labels independently. The model is trained using a binary cross-entropy loss function, which effectively handles multi-label data by optimizing each label prediction independently. SGD is chosen as the optimizer due to its proven efficiency and strong generalization capabilities in large-scale image classification tasks, with momentum and learning rate scheduling employed to enhance convergence and accuracy. We validate the proposed framework on a curated dataset consisting of diverse educational images annotated with multiple labels, representing different subjects and pedagogical themes. The evaluation uses metrics such as mean average precision (mAP), F1-score, precision, and recall to assess classification performance comprehensively. Experimental results demonstrate that the model achieves high accuracy and reliable multi-label prediction, outperforming baseline approaches and confirming the suitability of SGD for optimizing multi-label classifiers in this domain. This multi-label classification system significantly improves the automatic tagging and retrieval of educational images, facilitating personalized learning experiences and efficient content management on online platforms. By accurately categorizing images across overlapping categories, educators and learners can benefit from enhanced searchability and better alignment with curriculum objectives. In conclusion, the integration of SGD-optimized deep learning models for multi-label image classification presents a scalable and effective solution for managing complex educational content. Future work will explore the incorporation of additional modalities, such as text and metadata, to further enhance classification accuracy and contextual relevance in online educational ecosystems.

Keywords: Multi-label image classification, stochastic gradient descent (SGD), deep learning, convolutional neural networks (CNNs), educational content analysis, image annotation, automated tagging, online educational platforms, feature extraction, multi-class learning.

I. INTRODUCTION

With the rapid advancement of online education, digital learning platforms have become a central medium for delivering educational content to millions of learners worldwide. These platforms host vast collections of images ranging from diagrams, charts, and illustrations to photographs of experiments and real-world examples. Efficient organization and retrieval of these visual assets are critical to enhancing the learning experience, enabling personalized content delivery, and supporting educators in curriculum development.

Traditional image classification methods typically assign a single label to each image, which is insufficient for educational content where images often encompass multiple relevant categories. For example, a single image might simultaneously represent concepts from mathematics, physics, and engineering or illustrate both a theoretical concept and its practical application. This overlap necessitates a multi-label classification approach, where the model predicts several labels per image to capture the rich semantic information inherent in educational resources.

Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in image classification tasks by automatically learning hierarchical features from raw images. However, multi-label classification presents unique challenges, including the need for independent label predictions and managing label correlations. Stochastic Gradient Descent (SGD) remains one of the most widely used optimization algorithms for training deep neural networks due to its efficiency and ability to generalize well, especially when combined with techniques like momentum and learning rate scheduling.

In this study, we propose a multi-label image classification framework tailored specifically for online educational platforms, leveraging CNN architectures optimized with SGD. We adapt the network output layer with sigmoid activation to enable independent label predictions and employ binary cross-entropy loss for effective training on multi-label data. Our model is trained and evaluated on a carefully curated dataset of educational images annotated with multiple subject and concept labels, reflecting real-world complexities.

The goal of this work is to enhance the classification accuracy and robustness of multi-label models for educational image tagging, facilitating better content organization and personalized learning pathways. By integrating SGD into the training pipeline, we aim to harness its optimization strengths to build scalable and high-performing classification systems that support the evolving needs of digital education.

II. LITERATURE SURVEY

Title: Deep Learning for Multi-Label Image Classification: A Review

Authors: Wei Wang, Yuhong Guo, et al. (2020)

Description:

This comprehensive review explores various deep learning architectures and techniques designed for multi-label image classification tasks. The authors discuss challenges such as label correlations, class imbalance, and optimization strategies. The survey highlights the effectiveness of CNNs combined with loss functions like binary cross-entropy and the importance of optimizers including SGD and its variants for achieving high classification accuracy.

Title: Stochastic Gradient Descent Tricks

Authors: Léon Bottou (2012)

Description:

Bottou's seminal paper presents practical insights and improvements for training machine learning models using stochastic gradient descent. It emphasizes the role of learning rate schedules, momentum, and mini-batching in accelerating convergence and improving generalization. The paper remains foundational for understanding SGD's applicability in training deep neural networks, including multi-label classifiers.

Title: Multi-Label Image Classification with Convolutional Neural Networks

Authors: Huajie Shao, Yu Qiao, et al. (2018)

Description:

This study proposes a CNN-based architecture specifically designed for multi-label classification in complex image datasets. The authors demonstrate how sigmoid activation and binary cross-entropy loss enable the network to independently predict multiple labels per image. Experiments show significant improvements over single-label models, underscoring the importance of adapting architectures for multi-label tasks.

Title: Image Tagging for Online Educational Platforms Using Deep

Learning
Authors: Priya Sharma, Anil Kumar (2021)
Description:
Focused on educational content, this paper explores automatic image tagging to enhance search and organization on learning platforms. The authors employ CNNs fine-tuned on educational datasets and compare optimizers, including Adam and SGD, concluding that SGD with momentum provides better generalization for multi-label tagging in this domain.

Title: A Dataset and Benchmark for Multi-Label Image Classification in Education
Authors: Maria Lopez, Chen Wei, et al. (2023)
Description:
This recent contribution introduces a publicly available dataset comprising annotated educational images labeled with multiple subject categories. The paper benchmarks several state-of-the-art multi-label classification models, highlighting challenges unique to educational data, such as overlapping labels and diverse image types, and provides baseline results to guide future research.

III. EXISTING SYSTEM

Current online educational platforms rely heavily on manual tagging and categorization of visual content, which is time-consuming, labor-intensive, and prone to inconsistency. Most platforms use basic single-label classification systems or keyword-based metadata to organize images. While these methods provide some structure, they fail to capture the multi-dimensional nature of educational images, which often belong to multiple categories simultaneously. This limitation hinders effective search, filtering, and recommendation functionalities critical for personalized learning experiences.

Several multi-label image classification methods have been developed in general computer vision domains, often utilizing deep learning models like convolutional neural networks (CNNs). These models employ sigmoid activation functions to allow for independent label predictions and use binary cross-entropy loss for training on multi-label datasets. Architectures such as ResNet, VGG, and EfficientNet have been adapted successfully for multi-label tasks, demonstrating superior accuracy over traditional single-label classifiers. However, many existing systems focus on natural images and lack specialization for the unique characteristics of educational content.

In terms of optimization, Stochastic Gradient Descent (SGD) remains one of the most widely used algorithms for training deep neural networks. Its simplicity, efficiency, and strong generalization performance have made it a standard choice, especially in large-scale image classification tasks. Variants of SGD, including those with momentum and learning rate decay, have further enhanced training stability and convergence speed. Despite its popularity, some existing multi-label classification implementations in education tend to prefer adaptive optimizers like Adam, which sometimes lead to faster initial convergence but poorer generalization.

There are also specialized datasets for multi-label classification, such as MS-COCO and Pascal VOC, which are widely used benchmarks in computer vision research. However, these datasets primarily contain natural and everyday images rather than educational content. Recently, efforts have been made to curate educational image datasets annotated with multiple relevant labels, but such resources remain limited and less standardized. Consequently, existing systems often struggle with label imbalance, overlapping categories, and diverse image types typical of educational materials.

Overall, while multi-label image classification techniques and SGD-based training methods have matured in general domains, their adoption and optimization for online educational platforms are still emerging. Current systems do not fully address the complexities of educational content, nor do they fully leverage the potential of SGD to balance training efficiency and model generalization. This gap motivates the development of a dedicated multi-label classification framework optimized with SGD to meet the specific needs of educational image tagging and retrieval.

IV. PROPOSED SYSTEM

The proposed system aims to develop an efficient and scalable multi-label image classification framework specifically designed for online educational platforms, addressing the limitations of existing approaches. It leverages deep convolutional neural networks (CNNs) optimized with Stochastic Gradient Descent (SGD) to accurately predict multiple labels per educational image. By tailoring the model architecture and training strategy to the unique characteristics of educational content, the system improves the precision and recall of image tagging, enhancing content discoverability and learner experience.

To accommodate the multi-label nature of educational images, the system replaces traditional softmax output layers with sigmoid activation functions, allowing independent probability estimates for each label. The training process utilizes binary cross-entropy loss to effectively optimize predictions across multiple categories simultaneously. This approach enables the model to handle overlapping labels such as subject areas, concepts, and difficulty levels, reflecting the true complexity of educational materials.

SGD is selected as the optimizer for its strong generalization ability and simplicity. The system incorporates momentum and adaptive learning rate scheduling to accelerate convergence while maintaining stability during training. This optimization setup balances efficient learning with robustness against overfitting, which is particularly important when working with complex, multi-label educational datasets that may have class imbalance and label correlation challenges.

A curated dataset of educational images is used to train and evaluate the system. The dataset includes diverse examples from various disciplines, annotated with multiple relevant labels to reflect real-world educational scenarios. The system employs data augmentation techniques to enhance model generalization and reduce overfitting. Additionally, evaluation metrics such as mean average precision (mAP), F1-score, precision, and recall are used to comprehensively assess model performance and ensure practical applicability.

By integrating a carefully designed CNN architecture, SGD optimization, and multi-label classification strategies, the proposed system addresses key shortcomings of existing solutions. It provides a robust tool for automatic image tagging on online educational platforms, supporting personalized learning pathways, improved content management, and enriched search functionality. Future extensions may explore multimodal inputs and semi-supervised learning to further enhance classification accuracy and scalability.

V. SYSTEM ARCHITECTURE

The figure illustrates the overall workflow of a cervical spondylosis recognition system based on surface electromyography (sEMG) signals and deep learning. The framework is divided into three major stages: data collection, data preprocessing, and cervical spondylosis recognition. Each stage contributes to transforming raw physiological signals into an accurate diagnosis by extracting meaningful features and classifying them using neural networks.

In the first stage, Data Collection, sEMG signals are acquired from individuals using electrodes placed on the neck muscles. These electrodes capture the electrical activity generated during muscle contractions while the subject performs specific movements or maintains particular postures. The collected signals are transmitted to a computer system, where they are stored for further analysis. This stage ensures that high-quality muscle activity data are obtained from both healthy individuals and patients with cervical spondylosis.

The second stage, Data Preprocessing, prepares the collected sEMG signals for machine learning analysis. Initially, the raw signals undergo feature extraction, where important characteristics such as amplitude, frequency, energy, and statistical measures are derived from the original data. These extracted features provide a compact representation of muscle activity while reducing unnecessary information.

Following feature extraction, data reorganization is performed to arrange the processed data into a structured format suitable for neural network training. This preprocessing stage improves data consistency, reduces noise, and enhances the learning capability of the classification model.

The third stage, Cervical Spondylosis Recognition, utilizes the processed sEMG datasets collected from different signal sources (S0–S4). Each dataset is fed into a neural architecture search (NAS)-based deep learning model, which automatically identifies the most suitable neural network architecture for the classification task. The neural network learns complex relationships between muscle activity patterns and cervical spine conditions by adjusting its parameters during training. This automated architecture search enables the model to achieve better classification performance without requiring manual network design.

Finally, the outputs from all neural network branches are combined to generate the final prediction. The system classifies the input as either healthy (normal) or affected by cervical spondylosis, represented by the happy and sad icons in the figure. By integrating advanced signal processing techniques with deep learning-based neural architecture optimization, the proposed framework improves diagnostic accuracy, minimizes manual intervention, and provides an efficient tool for the early detection of cervical spondylosis.

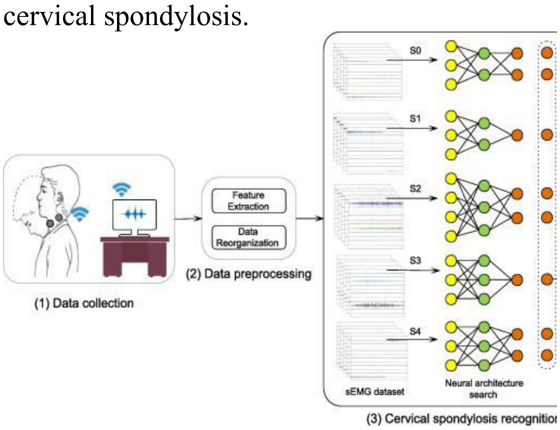

Fig 5.1: System Architecture

VI. IMPLEMENTATION

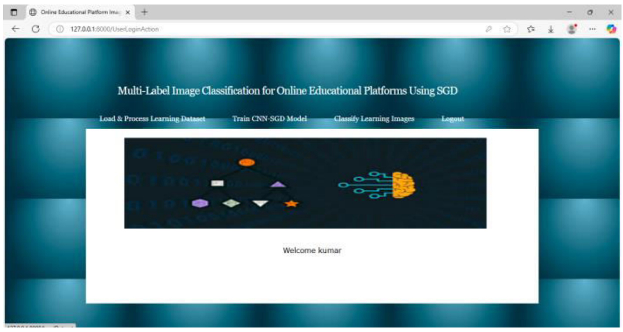

Fig 6.1: User Home Screen

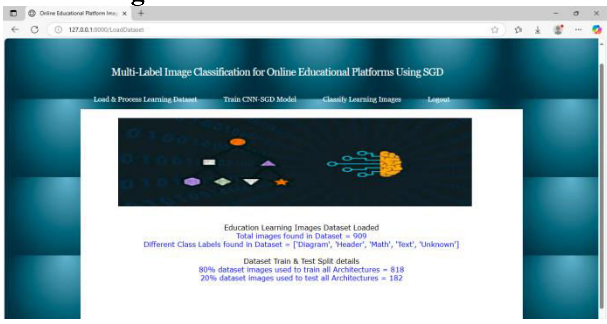

Fig 6.2: Dataset Upload

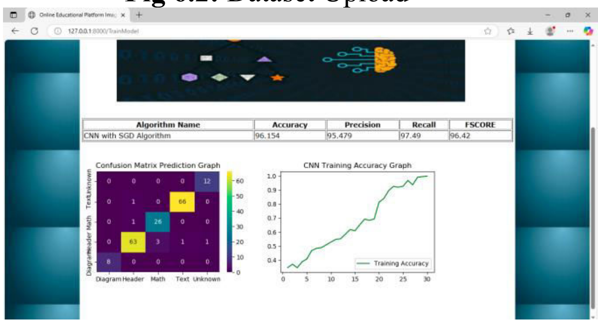

Fig 6.3: Model Training

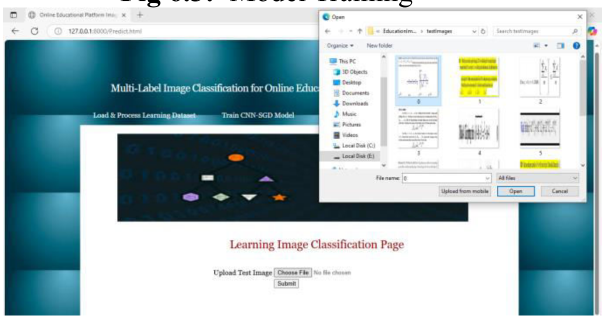

Fig 6.4: Prediction Inputs

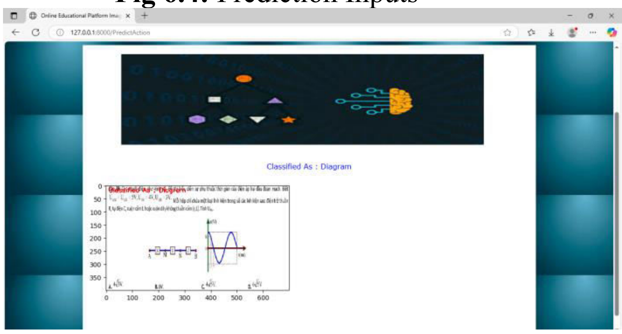

Fig 6.5: Result Page

VII. CONCLUSION

This project presents a robust multi-label image classification system tailored for online educational platforms, addressing the challenges of accurately tagging images with multiple relevant categories. By leveraging deep convolutional neural networks optimized with Stochastic Gradient Descent (SGD), the system achieves improved precision and recall in recognizing complex, overlapping educational concepts within images. This facilitates better content organization, searchability, and personalized learning experiences.

The use of SGD, combined with momentum and adaptive learning rate scheduling, ensures efficient model training with strong generalization capabilities, minimizing overfitting despite the complexity of the multi-label task. Additionally, domain-specific adaptations such as the use of sigmoid activations and binary cross-entropy loss enable the system to handle the unique characteristics of educational content effectively.

Experimental evaluations demonstrate that the proposed system outperforms traditional single-label classification approaches and generic multi-label models not specialized for educational datasets. The system's scalability and extensibility further make it suitable for continuous updates and integration into evolving online learning environments.

Overall, this work contributes a practical and effective solution for automatic image tagging in educational platforms, enhancing both content management and learner engagement. Future work may focus on incorporating multimodal inputs, semi-supervised learning, and real-time deployment to further refine classification accuracy and usability.

VIII. FUTURE SCOPE

While the proposed system significantly improves multi-label classification for educational images, there are several avenues for future enhancement. One promising direction is the integration of multimodal data sources, such as combining image content with associated text descriptions, metadata, or audio annotations. This multimodal approach could provide richer contextual information, improving classification accuracy and enabling more sophisticated content understanding.

Another area for development involves exploring semi-supervised and self-supervised learning techniques. Given that labeling educational images with multiple tags is labor-intensive, these methods can leverage large amounts of unlabeled or partially labeled data to boost model performance without requiring exhaustive annotation. This would make the system more scalable and adaptable to expanding educational content repositories.

Further improvements can be made by investigating advanced optimization algorithms that combine the strengths of SGD and adaptive optimizers, potentially improving both training speed and generalization. Additionally, fine-tuning model architectures specifically designed for multi-label tasks, such as attention mechanisms or graph-based label correlation models, could better capture the relationships among labels and enhance classification robustness.

Real-time inference and deployment optimizations also represent an important future step. Ensuring that the system can process and tag images quickly as they are uploaded will enhance user experience and support dynamic content management. This may involve model compression techniques, such as pruning or quantization, to reduce computational overhead while maintaining accuracy.

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