Comparison of Processing Time of Different Machine Learning Algorithm for Providing Digitization of COVID-19 Paper Application Forms

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Abstract*—Given Handwritten character recognition is an essential task in various domains, including optical character recognition (OCR), document analysis, and automated data entry. Convolutional Neural Networks (CNNs) have shown remarkable success in addressing this challenge by leveraging their ability to automatically learn meaningful features from raw input data. Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for analyzing visual data such as images. They have revolutionized the field of computer vision by achieving remarkable performance in tasks such as image classification, object detection, and image segmentation. the context of the COVID-19 pandemic, the efficient processing and management of COVID-19-related invoice documents have become crucial. These documents may contain critical information related to healthcare, supplies, and services provided during the pandemic. Ensuring accurate and efficient handling of such documents is essential for healthcareorganizations, government agencies, and businesses involved in pandemic response. To address these challenges and streamline theinvoice processing workflow, the framework known as Quash HuntOptimization with Bidirectional Encoder Representations from Transformers-enabled Deep Convolutional Neural Network (QHtO-BERT enabled Deep CNN) is proposed that leverages the power of BERT, to capture semantic information from invoice text. Google Optical Character Recognition (OCR) is an advanced technology developed by Google, enabling the retrieval of text from images or scanned documents. The process of text annotation usingNamed Entity Recognition (NER) involves the task of recognizing and categorizing named entities existing within a provided text. TheBERT-based approach significantly improves semantic understanding, while the optimized DCNN ensures feature extraction and classification tasks. The model's accuracy is elevated by harnessing the Hunting and Escaping characteristics within the QHtO algorithm. The performance of the QHtO-BERT- enabled Deep CNN method concerning accuracy, sensitivity, and, specificity stands at 94.7%, 95.92%, and 95.02%, respectively. The processing time required for conversion 90 COVID-19 PUI & CR forms is 8 minutes and 21 seconds that provide a commercially feasible solution as compared to a manual process.

***Keywords*— Invoice documents, BERT enabled Deep CNN, Google OCR, and Named Entity Recognition.**

I.INTRODUCTION

Invoice processing holds utmost significance for the financial department of any organization that involves handling and managing invoices received from vendors or customers, ensuring accurate recording of financial transactions, and facilitating timely payments or receipts [1].The COVID-19 pandemic has led to an increased demand for structured invoice documents related to activities and transactions associated with the pandemic response, such as medical supplies procurement, healthcare services, and emergency support.This variation poses difficulty inautomatically extracting organized data from unstructured documents during the process of invoice recognition and data entry automation [2]. Information extraction constitutes a correlated task which intented to autonomously retrieve targeted data from intricate documents. The existing literature concentrates on two main areas: extracting information from unstructured plain text [3] [4] and extracting from scanned documents [5]. The process of extracting information from plain text is not well-suited to handle the underlying complexity of document structure. This complexity goes beyond merely extracting text-related information and necessitates the inclusion of the original layout information [6].

To overcome this obstacle, prior text extraction tools, such as OCR, [7] are commonly employed. OCR is a tool for converting various types of texts, including scanned converting study documents, PDF files, or digital cameraphotos into editable and searchable data. OCR software recognizes the text content present in these documents and converts them into machine-readable text[7]. To address this issue, the development of innovative technologies and frameworks has become crucial. Leveraging advancements in Natural Language Processing (NLP) [9], businesses can now deploy sophisticated systems capable of recognizing and extracting structured information from unstructured invoicedocuments automatically. To tackle the challenges associated with unstructured invoices a novel framework was designed that utilizes an optimized BERT model, along with a Deep CNN classifier.

The framework's primary objective is to provide structuredoutputs, delivering critical invoice fields such as names of people, organizations, locations, dates, and more. The firststep involves collecting invoices that pertain to COVID-19- related activities and transactions. Following the data collection, the content extraction process utilizes Google OCR. Then the annotation of text using NER is performed. The collected data undergoes preprocessing before being introduced into the optimized BERT enabled Deep CNN classifier, where optimization is performed through the utilization of the QHtO algorithm. Subsequently, the trained model's evaluation will be carried out using a validation dataset to assess its performance in accurately extracting structured information from invoice documents. The main contribution of the research is outlined as follows:

- ✓ *Quash Hunt Optimization (QHtO):* The QHtO algorithm is formulated by integrating the hunting behavior of hawks [10] along with the escaping characteristics of coati [11] which can handle complex optimization landscapes, Strives to achieve equilibrium between exploration and exploitation in the pursuit of the optimal solution, making it suitable for a diverse array of optimization problems.
- ✓ *Quash Hunt Optimization with BERT enabled Deep CNN (QHtO-BERT enabled CNN):* BERT is a potent pre-trained language model renowned for its comprehension of text context. By integrating BERT with a deep CNN, the framework can handle both text-based and image-based data. The CNN component can process images, such as scanned invoice documents, while BERT can process textual data present in invoices, such as descriptions and numbers. The hybrid approach allows the framework to handle diverse optimization tasks; QHtO contributes its exploratory abilities, enabling efficient and effective exploration of the search space, which is crucial in finding promising regions.

The document is categorized into several sections; Section IIdepicts the steps and difficulties involved in extracting data from invoice documents. In section III, this study includes the methodology, architecture, and data preprocessing procedures used to create our suggested framework. The findings and conclusions of the method are presented in Section IV. The conclusion of the research and the subsequentactions are detailed in Section V.

II. LITERATURE REVIEW

Manuel Carbonel *et al.*[12] employed a neural model designed for text localization and named entity recognition, effectively harnessing shared features to tackle interconnected tasks concurrently. In the case of unstructured documents, the model's capability to leverage utilizing common attributes to concurrently address interlinked tasks is limited due to the primary focus on handling a single independent task.

Arsen Yeghiazaryan *et al.* [13] introduced a Tokengrid method to extract data from unstructured documents. The authors employed two alternative 1D approaches for Line Item detection in invoices. The network architecture has a reduced number of parameters, resulting in quicker inference times during the model's evaluation phase. However, building a robust Tokengrid model demands a large and diverse datasetof annotated unstructured documents

Halil Arslan [14] deployed an application for Invoice Processing Based on Key Field Extraction. The author utilized a YOLOv5-based deep learning method for preprocessing which can handle a large volume of invoices efficiently and consistently, making it scalable to accommodate growing business needs. However, tuning the model to handle various invoices formats and layouts can be challenging and may require continuous optimization.

Hongbin Sun *et al.* [15] utilizes Spatial Dual-Modality Graph Reasoning for Key Information Extraction. This model demonstrates efficacy and resilience in managing intricate document layouts. but the ability to generalize to unseen or different document layouts and formats could be limited.

Zhanzhan Cheng *et al.* [6] employed amethod for Information extraction. Utilizing multi-modal features, such as visual, layout, and textual attributes, has the potential to enhance information extraction performance. Simultaneously, the information extraction process can serve as supervision foroptimizing text comprehension. However, generalizing across a wide range of font styles might be challenging, leading to potential errors in information extraction.

Problem Statement: Limited capability to handle interconnected tasks in unstructured documents due to a primary focus on a single independent task.Requires a large and diverse dataset of annotated unstructured documents to build a robust Tokengrid model. Difficulty in tuning the model for various invoice formats and layouts, requiring continuous optimization. Difficulty in generalizing across a wide range offont styles, leading to potential errors in information extraction.

The limitations that are mentioned above can be overcome using the proposed methods are as follows, The proposedmethod aims to create an efficient system for accurate information extraction from unstructured invoice documents, which can handle multiple tasks simultaneously by utilizing anoptimized BERT-enabled Deep CNN. The proposed method doesn't rely solely on dataset size but instead uses NER and preprocessing to handle unstructured invoice documentsefficiently. The proposed method utilizes an optimized BERT-enabled Deep CNN, which may provide more flexibility in handling different invoice formats and layouts. The proposed method's use of an optimized BERT-enabled Deep CNN may help improve text comprehension and reduce errors.

A. Challenges

- ➢ The process of annotating invoice documents is performed manually, which introduces the risk of errors and reliance on the annotator's knowledge and expertisein the data labeling task [16].
- ➢ In practice, invoices may contain noise, such as scanned artifacts or low-quality images, which can impact the accuracy of key field extraction. The application needs to handle and preprocess such noisy data effectively [14].
- ➢ Tokengrid may face challenges in comprehending complex contextual relationships within unstructured documents. This limitation can result in reduced accuracy when extracting information that heavily relies on broadercontext [13].
- ➢ Extracting information from documents with abundant visual content relies heavily on the complexity of the document's visual elements, including fonts, formatting,

and layout. If the document contains intricate visual structures, the font style embeddings may struggle to accurately capture and represent the information [6].

- While IGL-CNN considers spatial relationships, it may lack a deeper contextual understanding of the document content, leading to potential errors in key informationextraction, especially when dealing with ambiguous or complex text structures [15].

III. A FRAMEWORK FOR PROVIDING STRUCTUREDINVOICE DOCUMENTS USING OPTIMIZED BERT-ENABLED DEEP CNN

The main objective of developing a novel framework for unstructured invoice documents using optimized BERT- enabled Deep CNN is to create an efficient and effective system that can accurately process and extract relevant information from unstructured invoice documents. The initial step involves collecting unstructured invoice documentsrelated to COVID-19 from real-time sources. Next, the text is extracted from the collected data using Google OCR, the extracted text is annotated using NER to identify and categorized named entities such as names of people, organizations, locations, and dates. After annotation, the collected data undergo preprocessing to remove noise, standardize formats and handle inconsistencies. TF-IDF is a popular statistical technique employed in natural language processing and information retrieval which quantifies the significance of a term in a document to a larger collection of documents. The preprocessed data was then fed into an optimized BERT enabled deep CNN to make accurate and nuanced predictions. To optimize the classifier this research utilizes the characteristics of Golden Hawks and Coati. The final step involves evaluating the trained model using the validation dataset to measure its performance in correctly extracting structured information from invoice documents. The schematic representation of the optimized BERT-enabled Deep CNN for providing structured invoice documents is shown in Figure 1.

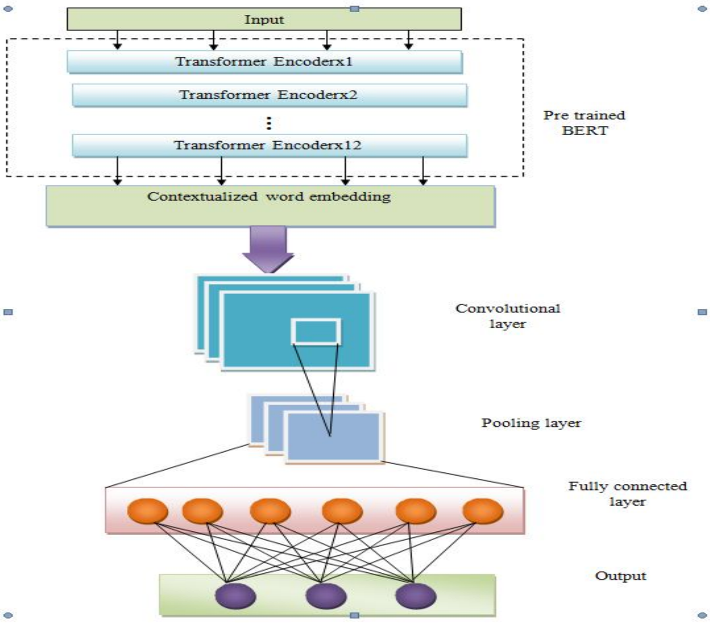


Figure: 1 Schematic representation of Optimized BERT enabled deep CNN

3.1 Input

The input for the proposed framework consists of 100 images or scanned copies of invoices related to COVID-19. Each image contains 16 labels, and the label has a dimension of $[16 \times 25]$. The total label dimension for all the images is $[100 \times 16 \times 25]$.

3.2 Extraction of Text Using Google OCR

The primary function of OCR [16] is to recognize and extract the textual content from the input documents so that the text can be processed, searched, edited, and analyzed by computers and software applications. In this proposed framework OCR is commonly used to convert physical invoices into digital formats, making them more accessible and editable.

3.3 Text Annotation using NER

NER holds utmost importance and serves as a critical task within information extraction.A natural language processing technique called NER involves locating and assigning categorizations to named entities [17] within a document, classifying them into specific groups like individuals' names, locations, seat no, date, flight no, village, district, pin code, and so on.

3.4 Preprocessing

Preprocessing refers to the initial steps taken to prepare raw data before it can be used for analysis or input into a machine learning model. In this research, preprocessing is done manually which includes text normalization; removing special characteristics, and handling missing values.

3.4.1 Text normalization: Text normalization [18**]** is a crucial step in natural language processing which involves transforming text into a canonical or standardized form. The purpose of text normalization is to bring different variations of words or phrases to a

common representation, reducing redundancy and facilitating more accurate analysis and comparison of text.
3.4.2 Removing special characteristics: Removing special characteristics refers to the process of eliminating non-alphanumeric characters, symbols, and other non-textual elements from a piece of text during text normalization. By removing special characters, the text becomes cleaner and more focused on the essential content, making it easier to process and analyze.
3.4.3 Handling missing values: Handling missing values [19] is a crucial step in data preprocessing, applicable to various data analysis tasks.Missing values occur when certain data points are not available or are incomplete in a dataset.

3.5 Proposed Quash Hunt Optimization (QHtO)

Motivation
The QHtO algorithm combines the hunting characteristics of hawks [25] with the escaping traits of coati [26] to effectively navigate complex optimization landscapes. This algorithm seeks to achieve a harmonious blend of exploration and exploitation to locate the optimal solution and make a versatile choice for various optimization problems.
Inspiration
Parabuteounicinctus (Harris Hawks) are known for their social hunting behavior, where they cooperate in groups to increase their hunting success [14]. This social foraging strategy could inspire an optimization algorithm that incorporates cooperative behaviors or swarm intelligence principles, where multiple agents (representing solutions) work together to explore and exploit the search space efficiently.Quash are agile animals known for their problem-solving skills and ability to adapt to various environments. An optimization algorithm inspired by quash might focus on adaptability and exploration, using strategies similar to coati's ability [15] to explore new areas and quickly escape from suboptimal regions in the search space. Hawks are known for their focused hunting behavior (exploitation), while coatis exhibit agile and exploratory characteristics. By combining these traits, the hybrid algorithm can strike a balance between local exploitation of promising regions and global exploration to avoid getting trapped in local optima.Quash are known for their adaptability to different environments. Integrating adaptive strategies into the algorithm can respond dynamically to changes in the optimization landscape, making it more robust and versatile. The phases of the QHtO algorithm are discussed below
a) Solution Initialization: This method involves randomly generating solutions within the feasible region of the search space. Random initialization is simple and can help explore various regions of the space. In this scenario, the solution is initialized randomly as Y^{tH} .
b) Fitness Evaluation: The fitness function accepts a candidate solution as input and outputs a numerical number indicating how fit or effective the solution is. Regarding the optimization goals, a solution with a greater fitness value is better than one with a lower value. In this context, the fitness function is.

$$Fit\left(Y^{t+1}\right)=MSE\left(Y^{t+1}\right) \tag{7}$$

Phase I Exploration phase
During this phase, the algorithm focuses on searching the search for new, promising regions in the solution space that might hold more effective answers. The exploration phase seeks to diversify the search and avoid premature convergence to local optima.

$$Y^{t+1}=0.5\left[Y^{t}+R\left(X^{t}-J\cdot Y^{t}\right)+2E_{0}*\left(1-\frac{s}{s_{\max}}\right)\right] \tag{8}$$

Where Y^t is represented as the current solution, Y^{t+1} is updated solution, R is denoted as the random number [0, 1], the current iteration is expressed as s , the maximum number of iterations is denoted as $s_{\max}$, E indicates the escaping energy,and X^t is represented as a neighbor solution or competing solution.
Phase II Exploitation phase
The process of intensifying the search around promising solutions or regions in the solution space is known as the exploitation phase. The primary goal of exploitation is to focus on refining the solutions to converge toward optimal or near-optimal solutions. The exploitation phase works in conjunction with the exploration phase, where the algorithm diversifies the search to discover new and potentially better regions of the solution space.

Case1 $R \geq 0.5$ & $E \geq 0.5$.

This case implies that both exploration and exploitation are emphasized in the optimization process. The exploitation rate is higher than 0.5, indicating a significant focus on refining and improving the solutions based on their local neighborhoods. At the same time, the exploration rate is also higher than 0.5, ensuring that the algorithm continues to discover novel areas within the solution space, preventing confinement to local optima and discovering potentially better solutions.

$$Y^{t+1}=\frac{1}{2}\left[4\cdot RY^{t}+(1-2R)\left(Y^{t}_{global}-Y^{t}_{pers}\right)+X^{t}-E*\Delta XY\right] \tag{9}$$

Where Y^{t}_{perss} indicates the personal Best Solution, ΔXY is represented as the difference in the distance between Y^t *and* X^t .

Case 2 $R < 0.5 \& E \geq 0.5$.

In this case, the exploitation-focused strategy, the algorithm's search process has enough energy to escape from suboptimal regions in the solution space. This escape mechanism helps the algorithm for discovering global optima or nearly optimum solutions by avoiding becoming stuck in local optima.

$$Y^{t+1} = X^t - E * \left[J \cdot * X^t - Y^t \right] \tag{10}$$

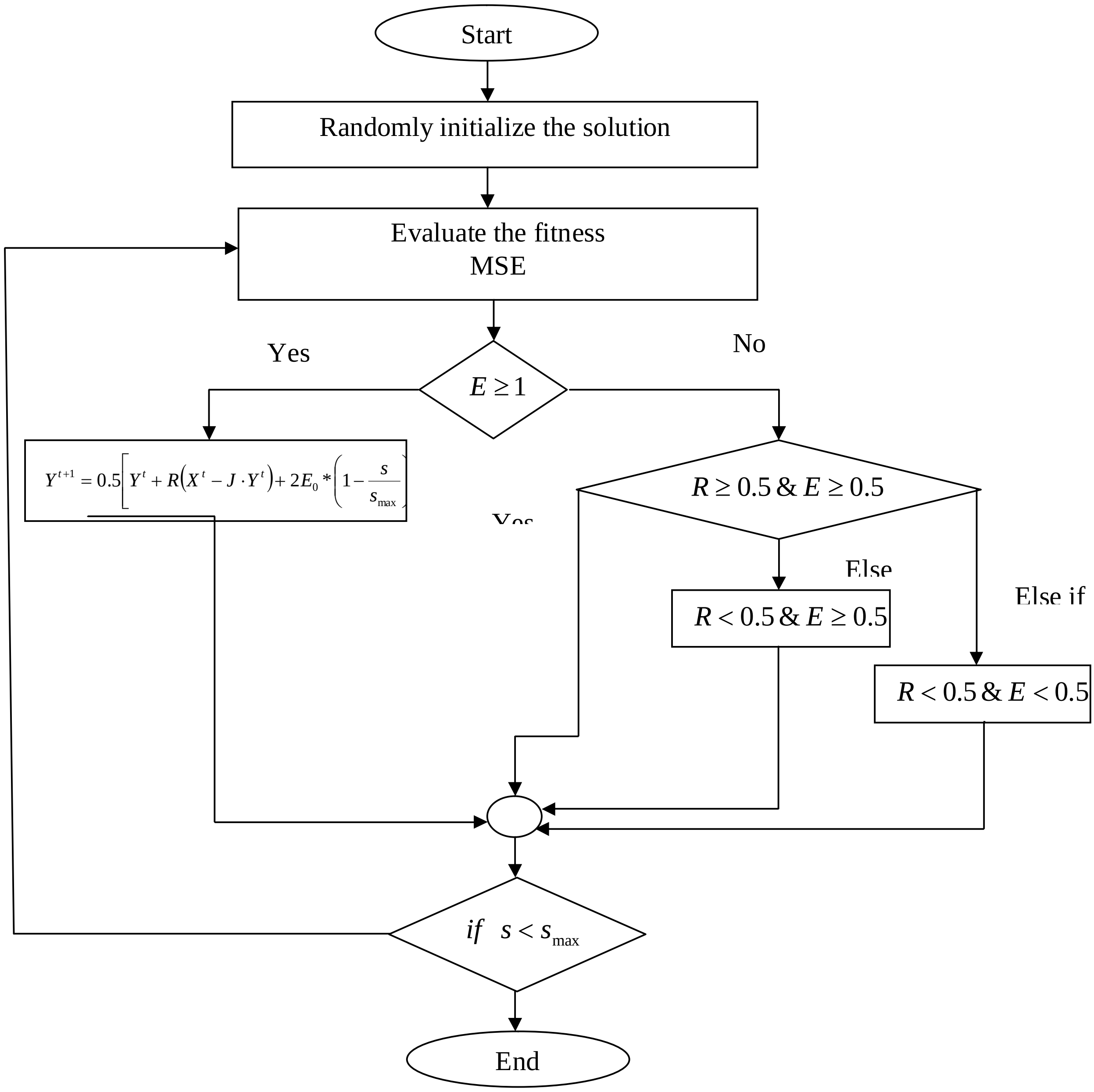
$$Y^{t+1} = X^t (1 - E * J) + E \cdot Y^t \tag{11}$$

Case3 $R < 0.5 \& E < 0.5$,

In this case, the optimization algorithm is predominantly focused on exploitation, refining the solutions around known good regions. This approach aims to fine-tune the solutions and refine them based on their immediate surroundings

$$Y^{t+1} = \begin{cases} Y^t \ ; if \ \ Fit(Y^{t+1}) < Fit(Y^t) \\ Y^{t+1} \ ; Otherwise. \end{cases} \tag{12}$$

Where Y^t denotes the updated position which indicates that the minimum fitness value improves the solution accuracy and performance. The proposed QHtO optimization is used to train the Deep CNN classifier.



IV. RESULT AND DISCUSSION

In this research, the QHtO-BERT enabled Deep CNN is developed for data extraction from invoice documents lacking structured formatting and the goal is to build an intelligent system that can accurately and efficiently extract relevant information from invoice documents. The method's results and discussion are outlined as follows.

4.1 Experimental Setup

The QHtO-BERT enabled Deep CNN was executed using the dataset on a Windows 10 machine with 8GB of RAM, utilizing MATLAB software.

4.2 Dataset Description

The dataset used for theQHtO-BERT enabled Deep CNN consists of a collection of documents relevant to COVID-19 which is designed to train and evaluate the QHtO-BERT enabled Deep CNN model that combines the QHtO-BERT and Deep CNN for named entity recognition. The dataset comprises 100 numbers of samples, each containing text data and corresponding 16 labels.

4.3 Performance Metrics

The parameters for measuring the efficacy of information extraction in unstructured invoice documents are discussed as follows,

4.3.1 Accuracy

Accuracy is characterized as the proportion of accurately classified instances to the overall number of instances within the dataset and it is mathematically assessed as follows:

$$accuracy = \frac{P_{TP} + P_{TN}}{P_{TP} + P_{TN} + P_{FP} + P_{FN}} \tag{13}$$

4.3.2 Sensitivity

Sensitivity measures the percentage of positive occurrences that the model properly classifies as positive. Mathematically sensitivity is expressed as,

$$sensitivity = \frac{P_{TP}}{P_{TP} + P_{FN}} \tag{14}$$

4.3.3 Specificity

Specificity represents the percentage of real negative events that the model accurately classifies as negative and is evaluated as,

$$specificity = \frac{P_{TN}}{P_{TN} + P_{FP}} \tag{15}$$

4.4 Performance analysis

The effectiveness ofQHtO-BERT enabled DCNN model is computed using the dataset and the TP metric. For epoch sizes of 100, 200, 300, 400, and 500, the TP values 50, 60, 70, 80, and 90 are taken into consideration.

4.4.1 Performance analysis for QHtO-BERT enabled Deep CNN with TP

The methods utilized for comparison encompass K-Nearest Neighbor (KNN) classifier (B_1) [27], Decision Tree (DT) classifier (B_2) [28], Deep CNN (B_3)[29], BERT CNN (B_4)[22], BERT CNN with Harris Hawk Optimization (BERT CNN with HHO) (B_5)[30], BERT CNN with Coati Optimization Algorithm (BERT CNN with COA) (B_6)[31], and Proposed BERT enabled Deep CNN with QHtO.

4.4.2 Comparative analysis with TP

The figure represents a comparative assessment of the Deep CNN empowered with QHtO-BERT against current methods for detection accuracy, sensitivity, and specificity. At TP 90%, accuracy of the QHtO-BERT enabled DCNN method is 94.7%, showing an improvement of 2.53 % over B_1, 2.11% over B_2, 1.68% over B_3, 1.26% over B_4, 0.84% over B_5, and0.42 over B_6as shown in Figure 5(a).Similarly, at TP 90, the sensitivity of the QHtO-BERT enabled DCNN approach is 95.92% indicating an increase of 3.59% over B_1, 2.99% over B_2, 2.39% over B_3, 1.79% over B_4, 1.19% over B_5, and 0.59 % over B_6, as depicted in Figure 5(b).Additionally, Figure 5(c) demonstrates that the specificity of the QHtO-BERT enabled DCNN is 95.02% at TP 90, showing an improvement of 2.79% over B_1, 2.33% over B_2, 1.86% over B_3, 1.39% over B_4, 0.93% over B_5, and 0.46% over B_6.

4.4.3 Comparative Discussion

Within this section, the discourse revolves around the techniques used for structured invoice documents. Several existing methods, including KNN (B_1), DT Classifier (B_2), Deep CNN (B_3), BERT CNN (B_4), BERT CNN with HHO (B_5), and BERT CNN with COA (B_6) are employed for comparison. The existing methods have major drawbacks, such as Deep CNNs can easily overfit the training data especially, when the dataset is small or the model is too complex, in the DT classifier, slight changes in the data could lead to a completely different tree structure making decision trees unstable and KNN does not handle imbalanced data well, as it tends to favor the majority class, leading to biased predictions. To overcome these limitations, the QHtO-BERT-enabled Deep CNN is introduced.

Table 1 depicts a comprehensive comparison of the QHtO-BERT enabled Deep CNN with these existing methods, considering different training percentages the performance is assessed, with particular emphasis on achieving a TP of 90.

Table1. Comparative discussion

Methods	**Training Percentage 90**			
	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**	**Processing Time (sec)**
B_1	92.305	92.475	92.368	1010
B_2	92.705	93.050	92.811	758
B_3	93.105	93.625	93.255	904
B_4	93.505	94.201	93.698	805
B_5	93.905	94.776	94.141	670
B_6	94.305	95.351	94.584	530
Proposed method	94.705	95.927	95.027	501

V CONCLUSION

In this research, the framework combines the power of BERT's contextual understanding with the deep convolutional neural network's image processing capabilities to efficiently extract structure information from COVID-19 re-invoice documents. The optimized BERT model significantly improved the performance of the deep CNN classifier, enhancing its ability to handle complex and varied invoice layouts. The framework demonstrated robustness in handling different invoice formats, even when dealing with scanned images of this study invoices. Furthermore, the comparative analysis with conventional methods showcased the superiority of QHtO-BERT enabled Deep CNN framework, outperforming traditional approaches. The achieved values for accuracy, sensitivity, and specificity were 94.7%, 95.92%, and 95.02%, respectively. For conversion 90 COVID-19 PUI & CR application forms into electronic form, it has taken 8 minutes and 21 seconds which is relatively less time of conversion and can provides commercially feasible solution as compared to manual process. 7% error is reported by the use of proposed automatic conversion system and 0% error can be maintained after corrective support of software to user. Subsequent efforts might center on expanding the framework's capabilities to handle multilingual invoices, handling unclear data, and exploring potential integration with blockchain technology for enhanced security and transparency in invoice processing workflows.

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