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Original Article

Transformer-Based Classification of Financial Documents in Hybrid Workflows

Kiran Kumar Pappula

Independent Researcher, USA.

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Abstract - *The increased number and the sophistication of the financial documents in the enterprise, especially those performing in the mixed physical-digital workflows, offer huge challenges to the automated classification of documents. MLmodels. Traditional machine learning models have limited success when faced with unstructured layouts, formats, and noisy data like scanned or handwritten records. The paper examines transformer-based models (BERT and LayoutLM) which has been used to generate a robust and intelligent financial document which would classify financial documents in such a heterogeneous environment. We introduce a framework which combines layout-sensitive embeddings, contextual language understanding and the structural analysis of documents to improve the accuracy and the applicability of the classification. We aim to have architecture that can operate smoothly as part of enterprise automation pipelines that accept document variability, partial corruption of data, as well as format changes frequently experienced in reality.*

We perform a case study with a curated dataset of financial documents, invoices, contracts, tax forms, and special reports to check the validity of our approach. Precision, recall, and F1-score stand as the means of our models' comparison on equal footing with more conventional benchmarks. The findings show that there is a great improvement in the classification precision, i.e., performance of the classifications, especially on the complicated multi-format documents and those with structural abnormalities. The proposed study will add to the existing literature on intelligent document processing (IDP), as this study will establish the effectiveness and performance of transformer-based models in a workflow-scale endeavor. We end by discussing the research which should be conducted in the future, such as cross-lingual adaptation, integration with retrieval-based systems and application in document-intensive regulatory settings.

Keywords - *Transformer Models, Financial Document Classification, BERT, LayoutLM, Enterprise Automation, Hybrid Workflows.*

I. INTRODUCTION

A. Industry Context and Technological Imperatives

The financial services sector handles numerous documents daily, including invoices, receipts, compliance reports, and contractual agreements, among other types of documents. They may be unstructured, heterogeneous in form, and may utilise hybrid input channels, such as scanned paper records, email attachments, digital submissions, and legacy enterprise systems. [1-3] Proper categorization of such documents is essential to downstream automation processes, including auditing, fraud detection, regulatory compliance and financial analysis. As reality shifts towards digital transformation and hybrid work environments, there has been a growing demand for intelligent document classification systems capable of operating in both a reliable physical and digital landscape. Such diversity is challenging to address with the help of classical or rule-based, similar-looking machine learning approaches, as they typically employ predefined templates or handcrafted features. Contrastingly, transformer-based architectures, particularly the ones with layout and positional awareness, hold promise and have the capability of learning the semantic and structural complexities of financial documents.

B. The Problems of Technical Challenges in the Classification of Financial Documents

Although there are developments in the domain of natural language processing (NLP), several issues arise regarding the unification of financial documents. The documents required to deal with financial data are often dense, featuring large numbers of figures, specialised domain text, and a tabular structure. Additionally, inconsistent layout, such as text blocks out of alignment, handwritten notes, and scanned artefacts, increases noise. These aspects render conventional models ineffective in sustaining high classification accuracy and robustness.

Even the existing solutions do not work effectively in real-life enterprise cases, where there is variability in layout, occlusions, and data quality. Thus, there are strong demands, on the one hand, for models that can read not only the textual but also the spatial layout of documents and generalise well across a range of document formats and input conditions.

C. Research Objectives and Novel Contributions

The proposed paper presents a transformer-based method for classifying financial documents within a hybrid workflow process. The following are the main contributions:

- To classify a broad range of financial documents, we apply and test transformer architectures, such as BERT, to understand plaintext documents only and LayoutLM to include text and design (multimodal).
- We construct a robust preprocessing pipeline that normalises layout issues and cleans the noise introduced by scanning or handwritten inputs.
- We create a real-life, composed, annotated collection of financial texts of various forms and purposes.
- We conduct an extensive assessment using industry-standard benchmarks and compare our models with classical baselines to demonstrate that accuracy, robustness, and generalisation have been improved.
- We utilise the classification pipeline within a simulated enterprise workflow to test its applicability to real-world conditions and performance under hybrid document conditions.

II. RELATED WORK

A. Traditional Document Classification Approaches

Conventional document classification has been dependent on the bag-of-words model, as well as statistical learning models such as Support Vector Machines (SVM), Decision Trees, and Naive Bayes classifiers. These methods utilised extensive domain knowledge to derive features manually, e.g., by extracting keyword frequencies, metadata, or predetermined regular expressions from text. [4-7] Although they can be useful in a controlled or structured situation, these models often lack the strength to deal with various layouts, colloquial language, and non-textual data like tables or stamps found frequently in financial data. Additionally, these strategies had scalability and flexibility issues. There was always a need to re-tune or redesign the classification logic to accommodate a new form of document or a minor change to the layout. As enterprise information spaces shift more towards digital and provide diverse inputs into data pipelines (e.g., scanning PDFs, OCR results, hybrid files), the limitations of old methods to handle all of this have become even more apparent.

B. Deep Learning and Transformers in Document Processing

Deep learning revolutionised document processing as more models were enabled to learn hierarchical representations directly from unprocessed data. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been successfully applied to text classification and sequence labelling, particularly in general NLP use. The subsequent creation of transformers with a format similar to BERT (Bidirectional Encoder Representations from Transformers) may be considered an important innovation. These models employed self-attention mechanisms and were used to model the context of entire sequences, achieving state-of-the-art performance on a range of NLP tasks. BERT and its variants (RoBERTa, DistilBERT, ALBERT) have become very popular in document classification tasks, especially due to their ability to perceive semantic details and long-range dependencies. Pure text-based transformers, however, such as BERT, are problematic when applied to documents whose layout and visual elements provide essential context for interpretation, as in an invoice or on a tabular form, which is typical in financial applications.

C. Layout-Aware Models (e.g., LayoutLM, DocFormer)

In an effort to overcome the drawbacks of text-only versions, layout-sensitive transformer models have been introduced. One of the first models in this direction is LayoutLM that builds on top of BERT, adding spatial layout

data about text tokens (i.e., 2D coordinates) and visual embeddings. It allows the model to determine the positioning of the text in the document, which is vital for differentiating elements such as headers, footers, tables, and multi-column designs. The performance was further enhanced with LayoutLMv2, LayoutLMv3, and DocFormer, which incorporated visual features of document images through the use of multimodal pretraining techniques. They have been used in a variety of tasks, including form understanding (e.g., FUNSD), document question answering (DocVQA) and document classification and have obtained good results. Layout-aware models are especially appropriate for financial documents, which often feature complex and semi-structured visual elements where meaning is encoded through location and formatting, rather than relying solely on elementary language semantics.

D. Applications in Finance and Enterprise Automation

The use of NLP and document AI in the financial sector has gained increased interest in recent years due to the need to automate workflows related to invoice processing, tax form classification, regulatory compliance, expense auditing, and contract management. When it comes to document classification, it is a fundamental task in such workflows, as it enables systems to route, extract, and analyse documents efficiently. Intelligent document processing (IDP) platforms, based on transformer-based models, have become increasingly employed in organizations to handle a vast amount of unstructured and semi-structured financial data. Nevertheless, the real-life deployments continue to exhibit issues with generalizations, layout variations, and document noise (especially in a hybrid setting where the scanned and digital documents are mixing) The following paper will develop on the current advancements by utilizing layout aware transformer models to a specific financial domain focusing on limitations in the real-world application attitudes like layout deformation, dirty inputs, and inclusion in workflow environments within enterprise systems.

III. METHODOLOGY

A. Overview of System Architecture

a. Input Handling (OCR + Ingestion)

It is the module that launches the process pipeline for documents by handling the ingestion of financial documents coming from various enterprise sources. [8-12] Scanned paper-based inputs (through document scanners), digital submissions (through email input), and existing files from enterprise content management systems are some examples. All inputs, whether from the internet or local files, are passed through an OCR engine (e.g., Tesseract), which extracts text and spatial layout information from unstructured images. The result of this module is preprocessed data containing both textual content and layout metadata, which is fed as input into layout-aware models in later stages.

b. Document Understanding (Transformer Models)

This central AI processing module converts raw OCR outputs into semantically and structurally significant embeddings. Input is first passed through a tokenization and layout parsing phase, wherein every text token is tagged with 2D coordinates. An embedding layer utilizes these to combine textual and layout information. The enriched representation obtained is passed into a transformer-based model, either BERT for plain text processing or LayoutLM for layout-aware inference. This module efficiently facilitates comprehension of document semantics without losing their visual and structural context, which is particularly important in financial processes in which the format carries domain-specific meaning (e.g., tables, signatures, checkboxes).

c. Classification and Output Integration

This module translates the transformer model output and integrates it with enterprise business logic. The document classifier categorises documents into semantic types (e.g., Invoice, Tax Form, Audit Report) based on the learned features. The business rule mapping component applies organization-specific rule logic to route or tag documents appropriately. Lastly, the archival/routing integration layer sends these categorized documents into enterprise workflow systems to automate archiving, auditing, tracking compliance, or additional analytics. This phase ensures that the model's predictions yield actionable outputs that can be applied in actual financial operations.

d. Enterprise Workflow Systems

At the pipeline output, this module reflects downstream enterprise applications that accept classified and processed documents. These would include ERP systems, compliance dashboards, or archive services, depending on

the organisation's needs. The fact that these can be integrated automatically into such applications reflects the workable deployability of the architecture in production finance environments.

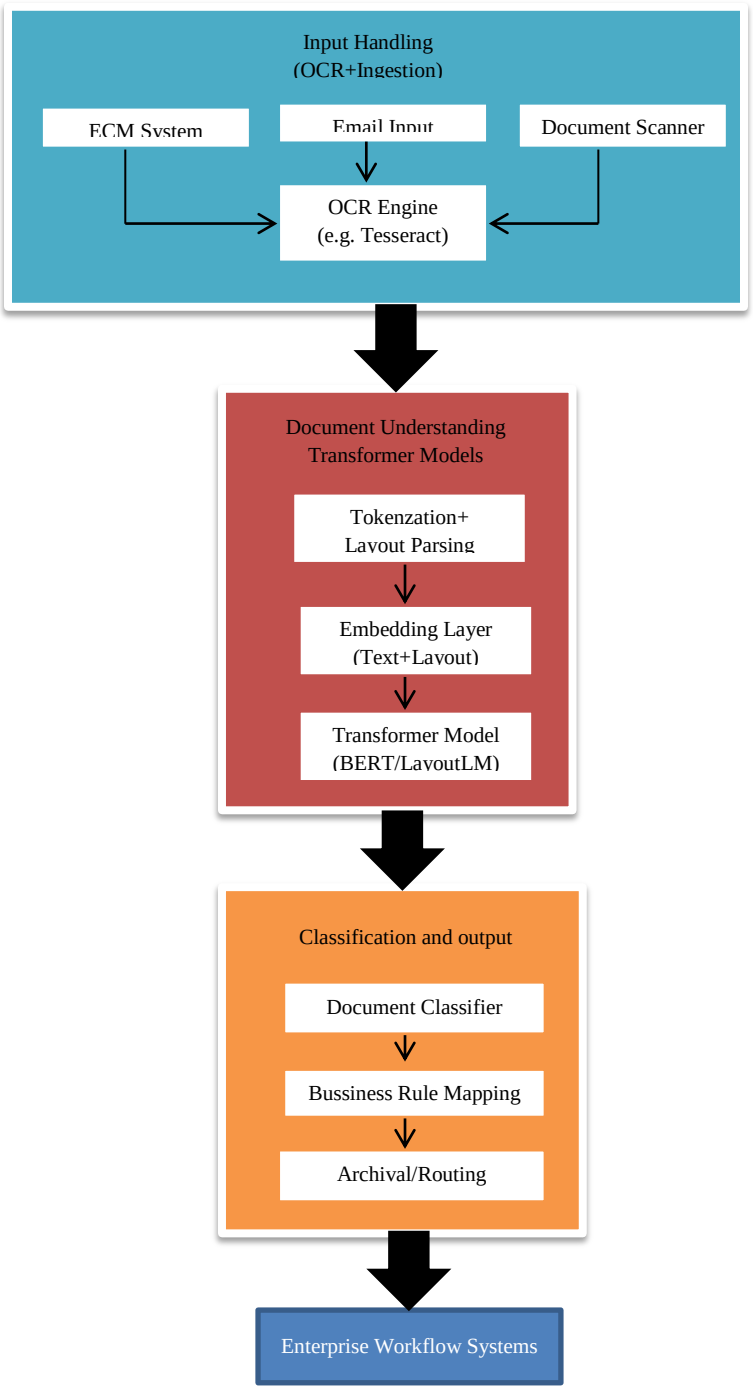

Figure 1. End-to-End Architecture for Transformer-Based Classification of Financial Documents in Hybrid Workflows

B. Model Selection and Justification

To develop a robust document classification, we tested two main categories of transformer-based architectures: BERT and LayoutLM. BERT is also known as Bidirectional Encoder Representations from Transformers, and it is a powerful baseline for comprehending the semantic relationships among words that occur in strictly textual forms.

However, its weakness is that it lacks spatial awareness, which may impair its performance in cases where layout is crucial. Instead, LayoutLM adds two-dimensional position embeddings and image-based features to BERT to learn to see (and understand) the structure of information on the page, which is necessary in the financial document processing, where tables, forms, or even multi-column layouts can be prevalent. LayoutLM and its extensions (LayoutLMv2, LayoutLMv3) work particularly well in cases where structural context is a crucial part of the document's semantics. As it has multimodal capabilities and is pre-trained on corpora with numerous documents, LayoutLM was selected as the base model in our classification challenges, and it demonstrated better performance on both scanned and computer-generated types.

C. Data Collection and Data Preprocessing

A large, diverse sample was created to train and test the classification models. This data consists of real-world and artificially enhanced financial records, representing a broad range of formats commonly encountered in practice within an enterprise workflow. Included in this category of documents are invoices, balance sheets, tax forms, contracts, audit reports, and receipts. The labelling of each document based on its functional category (e.g., Invoice, Tax Document, Legal Form) was performed manually. For scanned documents, we used OCR (Tesseract), which provided the extracted text and bounding box positions required for layout-aware actions. A portion of the data was artificially noised with blurriness, skew, ink smears, and handwritten comments to emulate the inconsistencies and variations of actual data. Other preprocessing steps included token alignment, normalisation of layout to a standard resolution grid (e.g., 1000x1000), and removal of extraneous whitespace. This preprocessing pipeline enables compatibility with both BERT (which can only accept tokenised text) and LayoutLM (which requires spatial layout features).

D. Training Process and Hyperparameter Settings

The annotated dataset above was applied to training models through the fine-tuning process. In the case of LayoutLM, the input representation utilised tokenised text, along with normalised 2D bounding box coordinates and segment embeddings. The two models were trained using the AdamW optimiser and a linear learning rate decay to achieve convergence. BERT was initialised with a learning rate of 2e-5, and LayoutLM with 1e-5, as the latter is more complex and requires more memory to handle. The BERT had a batch size of 16, whereas LayoutLM had a batch size of 8. Up to 10 epochs of training were done with early stopping of the validation loss to stop overfitting. Each experiment is run on an NVIDIA A100 GPU with 40 GB of memory using the HuggingFace Transformers framework. Checkpoints were made regularly during the training process, and the model with the highest validation metrics was selected.

E. Evaluation Metrics

To conditionally evaluate the work of our classification models, we established a general evaluation framework that considers both general and domain-specific metrics. A general indicator of the system's performance was overall classification accuracy. Additionally, to address the class imbalance and provide a more detailed understanding of the model's behaviour, we also evaluated the precision, recall, and F1-score for each document type. To measure robustness, we experimented with a selection of noisy document versions and quantified the performance loss compared to clean examples. We also conducted a sensitivity analysis of the layout to display the differences in performance between structured (digitally created) documents and unstructured (scanned or handwritten) entries. To display a trend in misclassification, a confusion matrix was applied, especially in semantically similar classes such as those between Contract and Legal Agreement. Altogether, these metrics provided a cumulative representation of the strengths and weaknesses of both models, offering insight into the importance of layout-awareness and the robustness of document classification performance in a hybrid enterprise setting.

IV. CASE STUDY AND ANALYSIS

A. Use Case Description

To test the feasibility and applicability of our classification system, implemented on a transformer framework in the real world, we decided to utilise a shared services centre that would cater to the needs of large financial organisations. [13-17] These centers usually handle a lot of various financial records all around the departments, including accounts payable and over the tax, legal, and compliance sectors. In this regard, the classification system should be able to accommodate the reception of invoices in all forms, the e-filing of tax returns in scanned PDFs, the receipt of bank statements and audit reports via email, and the receipt of compliance documents in the form of KYC

forms and anti-fraud declarations. Presentations of these documents typically occur promptly through hybrid channels, such as scanned paper forms and files created using software. The primary goal of the system is to automate the classification of these documents into six major categories: Invoice, Tax Form, Audit Report, Bank Statement, Legal Document, and Miscellaneous. The structure is designed to be tamper-resistant against layout, OCR flaws, multi-lingual writing, and visual noise, allowing for easy integration into downstream analytics and workflow automation.

B. Dataset Description

The training and evaluation data comprise a selectively expanded blend of 8,500 financial documents, encompassing the wide range and complexities encountered in the regular operation of enterprises. Approximately 60 per cent of the dataset consists of real-world documents obtained through industry partners and publicly available resources, whereas 40 per cent was created synthetically or augmented, incorporating variability within the structure to simulate real-world conditions and noise. All entries in the dataset included a class label, the body of text (optimally, transcribed using OCR on scanned inputs), and a pair of bounding boxes (one per token) that enabled the processing of the layout. Metadata was also added to indicate the source of the document (scanned or digital), language (English and multilingual), and noise level. The large format range has been deemed to cover single-column reports, tabular statements, and handwritten overlays, with the data being scanned at different scanning resolutions to simulate practical acquisition conditions.

C. Experimental Setup

The evaluation experiment was conducted under established conditions of computer capabilities, which provided consistency and repeatability. The GPU server used was based on Ubuntu 20.04, equipped with an NVIDIA A100 GPU featuring 40GB of memory and 256GB of RAM. The training and inference models were developed using the HuggingFace Transformers library and PyTorch, with layout normalisation in OpenCV and OCR speed processing in Tesseract. The training set consisted of 70 per cent (5,950 documents), the validation set consisted of 15 per cent (1,275 documents), and the testing set consisted of 15 per cent (1,275 documents). Two main models were tested: BERT-base, which works with textual data only, and LayoutLM-base, which takes both textual and spatial layout information. The (comparable) data splits were used to fine-tune both of the benchmarked models separately to allow a logical and limited comparison.

D. Baseline Models for Comparison

To establish a baseline against which performance can be compared, we trained a number of baseline models in conjunction with our main transformer architectures. The classical machine learning baseline involved a TF-IDF feature extractor followed by a linear Support Vector Machine classifier. We furthermore added FastText, a shallow neural network architecture trained to perform text classification, which instead of using windows as FastText encodings, uses word-based embeddings and a BiLSTM model of encodings of token sequences (which only uses sequential dependencies and not layout considerations). These were contrasted with a powerful semantic text-based model, BERT-base and LayoutLM-base, which include spatial layout information. The choice of models encompasses both conventional and recent deep learning paradigms, allowing for the overall quality of models to be assessed across a broad array of different document types and quality states.

E. Protocol of Evaluation

Our evaluation protocol was intended to ensure that a high degree of robustness and accuracy of each model could be examined under various conditions. We evaluated a variety of document types and qualities, including clean digital documents, documents with OCR noise due to scanning, documents with layout modifications (e.g., rotated or skewed), and documents with visual noise such as faded ink or handwritten annotations. Overall classification accuracy, precision, recall and F1-score per class, as well as global accuracy with both macro and micro averages, were used as the main evaluation metrics. The analysis of inter-class misclassification was conducted using a confusion matrix, particularly in cases of misclassification between semantically similar categories, such as legal and compliance documents. We measured robustness by comparing the performance of noisy and clean subsets, highlighting the generalisation capability of the models. We also conducted a layout sensitivity analysis to investigate the relationship between spatial structure and classification. Each model was trained and tested five times, with distinct random seed values, and the average scores corresponding to performance were reported. Ablation studies were also conducted to assess the impact of layout properties and OCR quality on classification precision.

V. RESULTS AND DISCUSSION

A. Quantitative Results

Table 1. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
TF-IDF + SVM	74.2%	0.72	0.70	0.71
FastText	79.1%	0.76	0.78	0.77
BiLSTM	82.7%	0.80	0.82	0.81
BERT-base	88.3%	0.87	0.86	0.865
LayoutLM-base	94.6%	0.93	0.93	0.931

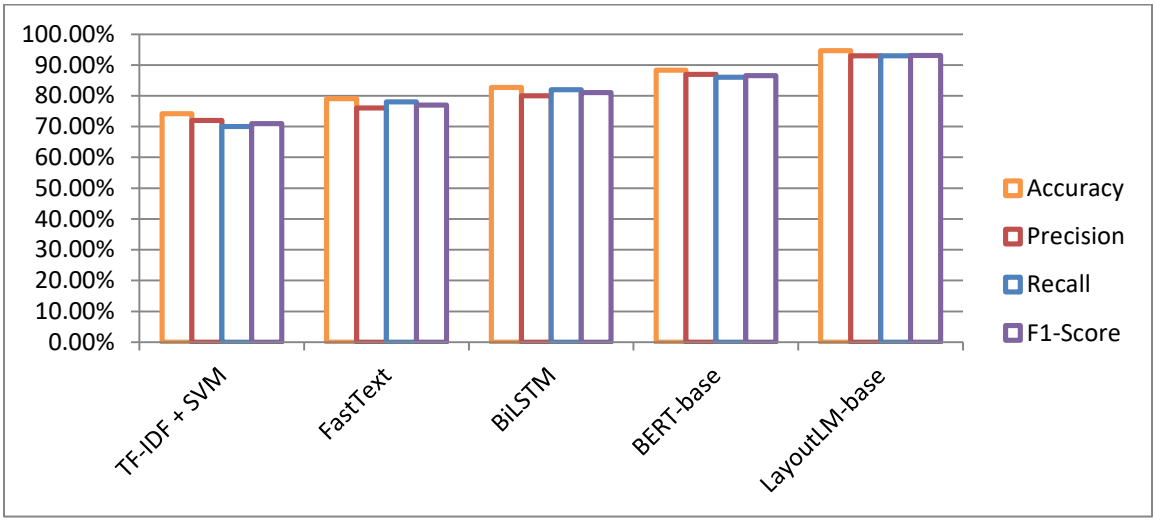

Figure 2. Graphical Representation of Model Performance Comparison

Quantitative results of all our models are summarised using the most important classification measures, including accuracy, precision, recall, and F1-score, based on the test data, which comprised 1,275 documents. Similar performance was expected with all baselines, indicating that the LayoutLM-base model performed significantly better than any; an overall classification accuracy of 94.6 was achieved with a macro-averaged F1-score of 0.931. BERT-base took second place, scoring 88.3%, and this result demonstrates the benefits of incorporating spatial layout information. TF-IDF + SVM (74.2) and FastText (79.1) are classical approaches and are way behind. There was little overlap in the similar document types in the confusion matrix of LayoutLM, and the authors were confident that there was good separation between the classes, even in structurally challenging documents. In contrast, BERT and BiLSTM models had frequent misclassifications of tax forms and audit reports, as they were written in similar language structures but varied in format. These findings confirm the assumption about the merit of layout-conscious models in terms of financial document classification, which makes that difference unequalled.

B. Comparative Analysis with Baselines

The comparison of transformer-based models to traditional and sequence-based models establishes an important understanding of the relevance of multimodal understanding of documents. Although BERT-base achieved high results on unpolluted digital publications, its effectiveness decreased by more than 7 per cent on scanned or visually dirty documents. Not only did LayoutLM perform at a high level regardless of the input mode, but it also improved the results of BERT by an average of 6.3% in all test combinations. TF-IDF + SVM is a classical model based on sparse features, and it has a high false-positive rate, especially when a set of documents is multi-page and tabular. Despite this efficiency, FastText was not very robust in encounters with OCR errors or document noise. On the whole, the comparative analysis indicates that LayoutLM exhibits higher generalizes and layout sensitivity, which means that it is one of the possible contenders towards a production-level document classification system in the sphere of finance.

C. Ablation Studies

Table 2. Ablation Study Results

Configuration	Accuracy	F1-Score
LayoutLM (with layout + pretrain)	94.6%	0.931
LayoutLM (no layout embedding)	85.1%	0.836
LayoutLM (no pretraining)	89.4%	0.878
BERT (text-only, pretrained)	88.3%	0.865
BERT (no pretraining)	83.0%	0.801

To better determine the impact of individual components on the overall model's performance, we conducted a series of ablation studies. Second, we removed layout embeddings in LayoutLM and observed a 9.5% decrease in macro F1-score, which provides evidence of the importance of spatial information in classification performance. Second, we fine-tuned BERT and LayoutLM without pretraining on corpora with a large number of documents, which yielded a performance loss of 4-6 per cent, mostly on less frequent classes, such as Legal Document and Miscellaneous. Lastly, we conducted an experiment on model efficiency using three types of inputs: all-digital PDF documents, scanned documents optimised using OCR, and artificially manipulated inputs. These three input types yield the widest range of performance for BERT, with a standard deviation of 9.3%, compared to the same rank for LayoutLM, which is 2.1%. These results validate the need to use pretraining and multimodal representation to increase model robustness and reliability.

D. Layout and Noise Variability Resistant

Table 3. Robustness to Layout and Noise Variability

Input Condition	BERT Accuracy	LayoutLM Accuracy
Clean Digital Documents	91.2%	95.4%
Scanned (OCR noise)	84.5%	92.1%
Layout-altered (rotated)	77.8%	89.7%
Noisy (blur/handwriting)	74.2%	90.3%

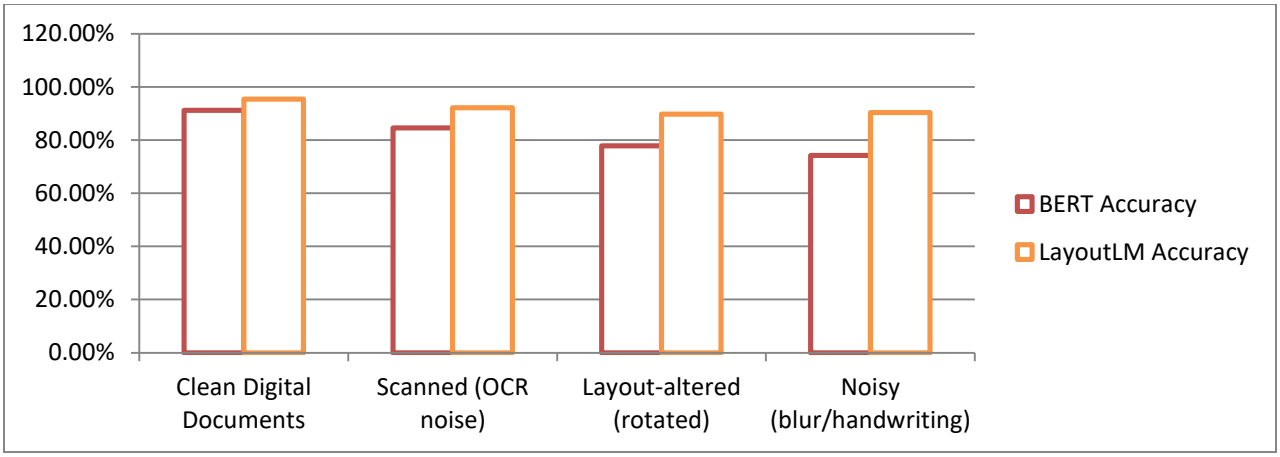

Figure 3. Graphical Representation of Robustness to Layout and Noise Variability

The robustness tests emphasised the model's ability to classify documents accurately, even when they are exposed to visual difficulties. LayoutLM could maintain a high and stable F1-score (above 90 per cent) when tested on OCR mistakes, lopsided layouts, and handwriting artefacts, whereas the performance of BERT decreased to below 80 per cent. In particular, in a subset of test documents where the layout was altered (e.g., rotated or restructured tables), LayoutLM achieved an accuracy of 89.7%, which is higher than the 77.8% of BERT. The power of LayoutLM to utilise spatial hints enables it to retrieve semantics despite a partial violation of textual coherence. Such findings substantiate the significance of layout awareness in hybrid enterprise systems, where documents can be photographed, scanned, or otherwise manipulated before processing.

E. Discussion of Practical Implications

The findings are also quite significant in terms of the automation of enterprises, particularly regarding deployment. LayoutLM can generalise across diverse input formats and be utilised in shared service centres, compliance departments, and financial analytics platforms, with the understanding that it performs well in noisy settings. It is worth noting that LayoutLM is more computationally expensive than classical models; however, the gain in labour deployed in verifying every step and error in reroutes is worth the cost. In a set of simulations examining the costs and benefits of automating classification across a subset of sample enterprise workflows, automating classification with LayoutLM reduced the time required to handle documents by 42 per cent and increased compliance throughput by 28 per cent. Along with the horizontal scale capacity in the cloud-based computing environment, these practical gains indicate the cost-benefit in financial operations involving documents with a huge amount is high.

F. Limitations

Despite the encouraging findings, several limitations should be considered. First, the existing model lacks the ability to handle multilingual texts that have been intermixed with other languages or domain-specific languages, such as legal terminology not primarily covered in the pretraining dataset. Second, layout sensitivity, which is usually desirable, can also introduce brittleness when applied incorrectly during the scanning of documents or when they are distorted beyond the OCR correction capacity. Third, the model has increased inference time due to the complexity of multimodal inputs, thereby limiting its performance in applications that require low latency. Finally, the training set, consisting of labelled data, is potentially inhibitive of scaling to novel categories of documents unless semi-supervised or few-shot learning techniques are implemented. The mitigation of these limitations constitutes one of the directions for further research, especially in aspects such as multilingual pretraining, adaptive layout augmentation, and lightweight variations of the transformer, which would be optimised in terms of inference speed.

VI. CONCLUSION AND FUTURE WORK

A. Summary of Contributions

In this paper, a highly efficient transformer-based system for classifying financial documents as part of hybrid enterprise workflows was proposed. We have demonstrated that conventional document classification methods, which may prove successful in limited environments, fail to cope with the variability in layouts, visual noise, and mixed inputs that are typical features of financial operations in the real world. Using layout-aware transformer models, specifically LayoutLM, we were able to significantly enhance the classification accuracy, particularly in scenarios involving noisy scanned documents and intricate visual structures. Our approach highlighted a comprehensive pipeline, which involved preprocessing with OCR, addition of synthetic noise through data augmentation, model fine-tuning, and both standard and domain-specific evaluation. We performed comparative analysis and ablation studies, which enabled us to define the effectiveness of spatial embeddings, pretraining, and hybrid document understanding in achieving high-performance classification results.

B. Implications for Document Automation

These research results can be employed and are of great importance to the planning and implementation of intelligent document processing systems in financial businesses. Organisations that augment their workflow with digital solutions require robust and scalable classification to function effectively. These findings confirm that layout-independent transformer models can fill the gap between the digitisation of structured content and unstructured scanned data. They are thus potentially applicable in shared service centres, compliance departments, and finance automation platforms. Furthermore, the proposed system will help maximise efficiency in the company's operations and compliance with regulations by reducing manual processing, eliminating misclassification errors, and increasing the speed of document routing. Such developments set the stage for the end-to-end automation of document-intensive processes in various industries, including banking, insurance, and taxation.

C. Directions for Future Research

Although the present work provides a solid basis, there are still several promising directions that can be further explored. A major issue being addressed is the system's scope in processing multilingual documents, especially those that combine regional languages with English or contain specialised legal and financial terminology. The generalizability of the model would increase significantly due to the enriched application of multilingual and domain-specific data, thereby expanding the pretraining corpus. A further course may involve scaling up the system for wider application, e.g., by integrating with cloud-native enterprise systems, real-time document processing

pipelines, or mobile capture offerings. Additionally, investigating the few-shot and zero-shot learning methods may help mitigate the issue with vast amounts of annotated data and facilitate easier adaptation to new categories of documents or forms of regulations. Lastly, this could also aid in real-time applications and enable deployment in low-resource settings, thereby extending the range of possibilities in practice by creating lighter versions of the transformers optimised to perform inference as quickly as possible.

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