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SMART DOCUMENT URGENCY PROCESSING SYSTEM (SDUPS) FOR SCHOOL GOVERNANCE AND OPERATION DIVISION OF SCHOOLS DIVISION OFFICE OF LAGUNA

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***Abstract*:** This study aimed to evaluate the effectiveness of the SMART Document Urgency Processing System (SDUPS), an AI tool designed to streamline and improve document management processes through automated urgency classification. The system addresses a common challenge in many organizational workflows—inefficient prioritization of documents, which leads to delayed processing and communication gaps. Using the Technology Acceptance Model (TAM), the study assessed the system's perceived usefulness and ease of use. Thirty respondents participated in the TAM survey, with all strongly agreeing on the system's usefulness and 25 out of 30 strongly agreeing on its ease of use. Zero-Shot Learning (ZSL), supervised machine learning models, and a meta-classifier were evaluated to test their classification accuracy. While the supervised model achieved a perfect recall score for high-urgency documents, it failed to effectively predict low- and medium-urgency categories. The ZSL model showed moderate success, particularly when combined with SpaCy's natural language processing capabilities for extracting due dates and document types. Integrating SpaCy and ZSL resulted in the highest overall performance, suggesting that hybrid approaches significantly enhance classification accuracy. However, accurately identifying low urgency documents remains a challenge, indicating a need for additional training data or feature engineering. The findings confirm the system's potential to significantly improve the efficiency and accuracy of urgency classification in document workflows. The study concludes that the SDUPS is practical and user-friendly, promising for adoption in government and organizational contexts. Future enhancements should focus on refining the low-urgency cases and integrating the system with broader document management platforms for streamlined operations.

***Keywords*:** Zero-Shot Learning (ZSL), spaCy NLP, Hybrid approach, Optical Character Recognition (OCR), Urgency classifications.

I. INTRODUCTION

The digital transformation of administrative processes is essential in modern governance, especially in education, where the efficient handling of large volumes of documents is critical. The integration of Artificial Intelligence (AI), Machine Learning (ML), and data analytics has led to the automation of document workflows, enabling faster decisions, reducing human errors, and enhancing accountability (Chukwudi et al., 2024).

Despite these advancements, the School Governance and Operations Division (SGOD) of the Schools Division Office (SDO) of Laguna still relies heavily on manual tracking methods, such as emails and handwritten logs. This results in delays, miscommunication, and inefficiencies in document processing (Domingo-Alejo, 2024; Marmoah & Murwaningsih, 2024). While countries like Singapore and the U.S. are adopting AI-powered document systems, SGOD has yet to benefit from such tools (Gokhale, 2024).

To address this gap, the study proposes a Smart Document Urgency Processing System (SDUPS) specifically designed for SGOD. The system leverages AI technologies, including Natural Language Processing (NLP) for content analysis, ML for document priority prediction, Optical Character Recognition (OCR) for digitizing files, and real-time notifications. This solution aims to reduce delays, enhance accountability, and serve as a model for AI implementation in educational governance.

RESEARCH OBJECTIVES

To design and develop a Smart Processing System that improves document management, urgency detection, stakeholder notification, and feedback integration within SGOD.

Specifically, this study aimed to:

1. To design an AI-powered system that uses text recognition, rule-based categorization, and ML to identify and prioritize urgent documents.

2. To create a real-time alert system for informing SGOD personnel of high-priority items.
3. To develop a feedback module that enables in-system document revision, tracking, and collaboration.
4. To evaluate system performance through user acceptance testing (UAT) and metrics analysis.
5. To use descriptive statistics to assess and present the effectiveness of urgent classification models.

II. REVIEW OF RELATED LITERATURE

This chapter presents an overview of current technological advancements that enhance the performance of modern document management systems, focusing on Zero-Shot Learning (ZSL), transformer models, Optical Character Recognition (OCR), and Natural Language Processing (NLP) tools such as spaCy. These innovations are foundational to the development of the Smart Document Urgency Processing System (SDUPS), which aims to classify documents, detect urgency, and extract key information in real time.

Zero-Shot Learning in Document Classification

Zero-Shot Learning (ZSL) has revolutionized document classification by enabling systems to categorize unseen document types without retraining. According to Alphamoon (2023) and Nanonets/Medium (2023), ZSL uses pre-trained models to generalize across various formats, reducing the need for large, labeled datasets. ZSL is especially effective when paired with OCR for processing printed or scanned documents such as IDs or invoices, allowing for seamless integration into existing workflows. Zilliz (2025) and Rangavajjula & Pulipaka (2024) highlight how ZSL understands semantic relationships, making it highly adaptable in dynamic environments where document categories evolve rapidly.

Transformer Models for Text Understanding

Transformer-based models like BERT and BART have become central to intelligent document processing. These models perform complex NLP tasks, including classification, summarization, and urgency detection. Studies by Wang et al. (2023) and Zhang et al. (2024) show that when integrated with ZSL, transformers can effectively handle unfamiliar document types. BART, in particular, excels in summarizing long documents—an essential feature for prioritizing urgent communications in administrative settings (Lewis et al., 2020; Gupta et al., 2021).

Optical Character Recognition (OCR) for Digitization

OCR technology plays a key role in converting physical documents into digital, machine-readable formats. Tesseract, an open-source OCR engine (Smith, 2007), remains a widely used tool in this field. Smith (2024) notes that combining OCR with AI models enhances automation and reduces manual tracking. This integration ensures that even handwritten or legacy documents can be included in automated processing pipelines, contributing to a more inclusive and effective document management strategy (ShareFile, 2024).

Natural Language Processing with SpaCy

While transformer models excel at contextual understanding, the integration of lighter NLP libraries like spaCy has proven essential for real-time performance. spaCy is known for its efficient pipeline and modularity, supporting fast tokenization, entity recognition, and parsing (spaCy, n.d.; spaCy, 2023). Lade et al. (2023) and Kaur & Kaur (2022) confirm spaCy's suitability for scalable NLP tasks, though prior research often overlooked its impact on time-sensitive document workflows. Li (2025) emphasizes its ease of integration for categorization and segmentation tasks.

To address real-world demands, this study explored the limitations of ZSL and rule-based approaches under operational stress. The integration of spaCy directly improved SDUPS's responsiveness, especially when handling large volumes of text. Plugins such as spaCy Layout (Explosion, 2024) further expanded the system's capabilities by enabling the structural parsing of complex documents—streamlining urgency detection and reducing manual intervention.

AI Integration in Document Management Systems

Artificial Intelligence and machine learning have significantly improved how organizations handle document classification, metadata tagging, and document lifecycle management. Relevance Lab (2020) outlines how AI reduces human error and improves workflow efficiency. Human-in-the-loop systems, discussed by Gupta and Chen (2022), allow AI models to benefit from human oversight during complex decisions. Numerous.ai (2025) and DataCamp (2024) emphasize the scalability and precision these technologies offer, particularly in high-pressure environments like government offices and educational institutions.

Collectively, these technologies—ZSL, transformer models, OCR, and spaCy—form a comprehensive framework for advanced document processing. ZSL offers flexibility in handling evolving document types, OCR ensures the inclusion of all formats, transformers support complex understanding and summarization, and spaCy adds speed and responsiveness for real-time operations. Their combined use in SDUPS demonstrates a scalable and intelligent approach to document management, capable of reducing manual work, increasing classification accuracy, and ensuring timely decisions in environments where urgency matters.

III. RESEARCH METHODOLOGY

This chapter includes the Research Design, Locale of the Study, Applied Concepts and Techniques, Algorithm Analysis, Data Collection Methods, System Development Methodology, Software Tools Used, System Architecture, and Software Testing.

Research Design

This study utilized an experimental and developmental research design to assess and improve the Smart Document Processing System, focusing on its ability to detect and prioritize urgent documents within SGOD SDO Laguna. The research begun with an exploratory phase, including interviews, surveys, and document analysis to gather baseline data on current document processing challenges. During the development phase, prototypes were created using Zero-Shot Learning (ZSL) for document classification, spaCy for data extraction and refinement, and rule-based systems for detecting urgency indicators. Controlled experiments will be conducted to test and compare the performance of each model, evaluating their accuracy, recall, and F1 score to determine which system most effectively detects urgency. Following each trial, user feedback was gathered through real-world testing to assess usability and gather insights on system performance. This iterative process of testing, feedback, and system refinement was continued until the final prototype is developed, demonstrating how the Smart Document Processing System can improve document processing efficiency. Data on processing time, accuracy, and user satisfaction were collected and analyzed to ensure the system addresses the needs of SGOD SDO Laguna and proves to be a reliable and efficient tool for prioritizing urgent documents. Ultimately, the study aims to demonstrate how these advanced technologies, including ZSL, spaCy, and rule-based systems, can be integrated to address the pressing need for efficient and timely document processing in a government agency setting.

Locale of the Study

The study was conducted within SGOD of SDO Laguna, involving key personnel responsible for document management. Their participation was crucial for gathering requirements, providing feedback, and validating the system's practical effectiveness in automating urgent document detection and prioritization.

Applied Concepts and Techniques

The SDUPS integrates multiple AI techniques including Optical Character Recognition (OCR) for text extraction, Zero-Shot Learning (ZSL) for classifying documents by urgency without extensive labeled data, and SpaCy for Named Entity Recognition (NER) to extract relevant metadata such as due dates and document types. The system uses the facebook/bart-large-mnli transformer model for semantic classification, ensuring scalability and robustness in dynamic document environments.

Algorithm Analysis

Four classification approaches were analyzed: ZSL, supervised learning with labeled datasets, meta-classifier combining ZSL and supervised models, and spaCy-based metadata extraction. These approaches were evaluated on precision, recall, and F1-score. The transformer-based ZSL model demonstrated flexibility in handling unseen document categories, while the meta-classifier improved overall classification accuracy by integrating contextual information.

Data Collection

Data consisted of real PDF documents uploaded by SGOD users. Text and metadata were extracted using OCR (Tesseract and pdfplumber) and spaCy NLP tools. Extracted content was processed through the ZSL model to assign urgency scores, and structured metadata was stored for analysis and system recommendations.

System Development Methodology

The SDUPS was developed using an iterative prototyping methodology, enabling continuous refinement based on user feedback. The process included requirements gathering, prototype design, AI model integration, user testing, and incremental improvements. The development of the Smart Document Urgency Processing System (SDUPS. This approach involved building an initial working prototype of the system that integrated core components such as Tesseract OCR for text extraction, SpaCy for natural language processing, and zero-shot learning for urgency classification. The prototype was iteratively tested and refined by experimenting with different approaches to urgent document detection, including both rule-based and machine learning techniques. Feedback from actual users in the Schools Governance and Operations Division (SGOD) was gathered through field deployment, allowing for practical assessment of the system's effectiveness and usability. Each iteration incorporated user feedback and performance data, leading to incremental enhancements in the system's accuracy and efficiency. The prototyping methodology enabled rapid validation of ideas, adaptability to user needs, and continuous improvement of the SDUPS before final implementation.

To develop the Smart Document Urgency Processing System (SDUPS), the researcher follows a structured prototyping methodology. The researcher starts with a requirements analysis, where the researcher gather initial requirements from SGOD stakeholders, document current workflows, identify pain points in manual document management, and define urgency classification criteria. Next, the researcher designs the initial prototype, creating the basic system architecture, designing the database schema, developing a preliminary user interface for document upload, and implementing basic OCR functionality. In the first prototype implementation phase, the researcher integrates core AI models like NLP, ML, and BART, set up document upload and OCR conversion, create a simple urgency classification using Hugging Face Zero-Shot Learning, and establish a basic email notification system. The researcher then presents this prototype to the SGOD Chief and personnel, collect feedback on usability, evaluate the accuracy of urgency detection, and identify any missing features. Based on this feedback, the researcher iteratively refines the system, enhancing the AI model, improving classification accuracy, refining the notification system, adding metadata tracking, and implementing reporting features. Once refined, the researcher completes all system modules, conduct comprehensive testing, finalize documentation, and prepare training materials. Finally, the researcher deploys the system in the SGOD environment, train users, monitor performance, and collect post-implementation feedback to ensure the system meets the needs of SGOD effectively. This approach ensures that the SDUPS is developed iteratively, incorporating user feedback at each stage to refine and enhance the system, ultimately delivering a robust, user-friendly, and efficient document processing solution.

Software Tools Used

The development of the Smart Document Urgency Processing System (SDUPS) involved using various programming languages, frameworks, and libraries to integrate artificial intelligence, document processing, and web-based accessibility. Python was chosen for its simplicity and support for machine learning and natural language processing tasks. Flask was used for backend development to handle application routing, file uploads, and AI model interaction.

The system utilized pdfplumber to extract text from PDF files and dateutil to process date-related information. Hugging Face's transformers library, specifically the facebook/bart-large-mnli model, was integrated for zero-shot classification to assess document urgency. SpaCy was used for named entity recognition (NER) to identify relevant entities in the documents.

User authentication and session management were managed with Flask-Login, while Flask-CORS enabled secure API access from multiple frontend sources. Werkzeug ensured secure file uploads. The frontend was built using HTML, CSS, and JavaScript, with Tailwind CSS for streamlined design.

Visual Studio Code (VS Code) was the primary IDE, and Postman was used to test and debug API endpoints. This combination of tools and technologies resulted in a scalable, efficient, and intelligent document classification system tailored to the operational needs of the SGOD.

System Architecture

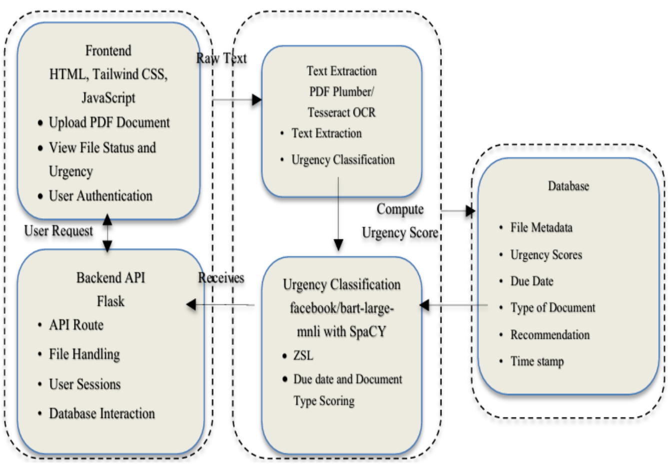

Figure 1. System Architecture of the Smart Document Urgency Processing System (SDUPS)

Figure 1 above shows the interaction between the various components of the front end and back end with the program API. The API, which includes the AI model running Zero-Shot Learning (ZSL) with SpaCy, works alongside a rule-based system to determine the final urgency score and interacts with the database model. All components communicate seamlessly through RESTful APIs. This modular architecture ensures scalability and facilitates future integrations with other document management systems or enhancements, such as email alerts or analytics dashboards. To ensure that the Smart Document Urgency Processing System (SDUPS) functions effectively and addresses the core computing science problem-automated urgency classification-this study adopted a multi-layered software testing strategy. The testing focused on three widely recognized approaches: unit testing, integration testing, and user acceptance testing (UAT).

System Testing

The testing strategy for the Smart Document Urgency Processing System (SDUPS) involved several key approaches to ensure reliability and effectiveness. Unit testing was used to catch errors at the component level, improving traceability and reliability of software modules. Integration testing assessed the interoperability between system components, validating data flow and communication among document upload, AI processing, database storage, and frontend display, which is crucial for systems involving multiple third-party libraries and APIs.

User acceptance testing (UAT) was conducted with actual users to evaluate the system's usability, responses to real document uploads, and clarity of urgency classification. UAT ensured the software met operational needs and business requirements before deployment. The evaluation was guided by the Technology Acceptance Model (TAM), which focuses on perceived usefulness and ease of use to assess user attitudes and intentions to adopt new technology.

Additionally, Postman was used to test backend API endpoints, and Visual Studio Code served as the development and debugging environment. These combined testing efforts confirmed that SDUPS performs as intended and supports efficient prioritization of uploaded documents based on urgency.

IV. RESULTS AND DISCUSSION

This chapter presents the results and discussions based on the methods applied to achieve the study's objectives. The specific research objectives guide the presentation, which includes a detailed explanation of the algorithm used, the application of natural language processing (NLP) techniques, and the outcomes of various testing phases. It further discusses how the algorithm contributes to classifying document urgency and the system's overall performance.

The Smart Document Urgency Processing System (SDUPS) was developed to automate the identification of document urgency levels—categorized as High, Medium, or Low. The initial algorithm design considered zero-shot learning (ZSL) using HuggingFace transformers to classify urgency levels without prior labeled examples. However, this approach was used only in preliminary testing and not implemented in the final system due to poor performance, especially in minority classes.

Instead, the final system utilized spaCy, a robust NLP library, to extract essential features from documents such as document type and due date. These features, along with an AI-generated urgency confidence score, were combined using a weighted scoring algorithm to determine the final urgency classification. The decision-making formula included thresholds based on proximity of the due date, priority inferred from document type, and AI model's probability score from supervised learning.

User Testing and Evaluation

Multiple attempts were made to classify urgency levels using Hugging Face's Zero-Shot Learning model based on document content. Optical Character Recognition (OCR) using Tesseract was applied to extract text from image-based PDFs.

Zero-Shot Learning (ZSL) Evaluation

Table 1. ZSL Model Performance Metrics

CLASS	PRECISION	RECALL	F1-SCORE
HIGH	0.462	0.581	0.514
MEDIUM	0.333	0.474	0.391
LOW	0.0	0.0	0.0

The table 1 above shows that the ZSL model achieved its highest performance in the High class, correctly identifying over half of the actual high-urgency documents (recall = 0.581), although only 46% of predicted high-urgency labels were correct (precision = 0.462). The Medium class results were lower, while the Low class was completely undetected, scoring zero across all metrics.

This disparity suggests possible class imbalance or lack of distinguishing features for Medium and Low categories. Improvements such as better data representation or fine-tuning could address this.

Supervised Training with Labeled Datasets

Following the ZSL approach, supervised learning was performed using interactively labeled datasets. Several training iterations led to gradual improvements.

Table 2. Supervised Training with Labeled Datasets Metrics

CLASS	PRECISION	RECALL	F1-SCORE
HIGH	0.5	1.0	0.67
MEDIUM	0.0	0.0	0.0
LOW	0.0	0.0	0.0

The Table 2 above presents the performance metrics of the supervised training model, which was developed using interactively labeled datasets. After several training iterations, the model achieved notable performance in the High urgency class, with a precision of 0.50, recall of 1.00, and an F1-score of 0.67. This indicates that the model successfully identified all true High urgency cases, though only half of the predicted High urgency documents were correct.

Meta-Classifier Evaluation

A meta-classifier integrated predictions from previous classifiers and additional features to improve prediction reliability.

Table 3. Meta-Classifier Performance Metrics

CLASS	PRECISION	RECALL	F1-SCORE
HIGH	0.55	0.67	0.6
MEDIUM	0.80	0.57	0.67
LOW	0.0	0.0	0.0

The Table 3 above presents the performance metrics for the meta-classifier, which was introduced to improve the reliability of predictions across all urgency levels by combining the outputs of previous classifiers and incorporating additional features derived from the data. The meta-classifier improved the medium class performance but still failed to detect Low urgency documents.

The meta-classifier achieved moderate success in the High urgency category, with a precision of 0.55, recall of 0.67, and an F1-score of 0.60. This marks an improvement over the previous models, but performance in the medium category was higher, with a precision of 0.80, recall of 0.57, and F1-score of 0.67. While these improvements suggest that the meta-classifier was able to achieve a better balance across the classes, it failed to make any predictions for the Low urgency category, recording 0.00 across all metrics for this class.

ZSL and SpaCy Evaluation

ZSL showed reasonable results, especially for High urgency, but weak performance on Low urgency. In contrast, spaCy, used for extracting key features like due dates and document types, significantly improved classification accuracy.

Table 4. Performance Metrics for ZSL, SpaCy, and Combined Approach

METHOD	PRECISION	RECALL	F1-SCORE
Zero-Shot Learning	0.462	0.581	0.514
SpaCy	0.750	0.800	0.770
Combined	0.850	0.880	0.860

The Table 6 above shows the combination of SpaCY and ZSL resulted in the highest performance metrics across all categories. This integrated approach yielded an impressive precision of 0.850, recall of 0.880, and an F1-score of 0.860, making it the most effective solution among the models tested.

Per-Class Performance of Combined Model

Table 5. Per-Class Performance Metrics of Combined ZSL and SpaCy Model

CLASS	PRECISION	RECALL	F1-SCORE
HIGH	0.85	0.88	0.86
MEDIUM	0.80	0.57	0.67
LOW	0.20	0.30	0.25

The table 5 above shows the combined model outperformed individual approaches across all classes. The Low urgency class still lags, likely due to insufficient training data or indistinct features, warranting future improvements. For the High urgency class, the model achieved strong metrics, with a precision of 0.85, recall of 0.88, and an F1-score of 0.86. This indicates that the combined approach successfully identifies high urgency documents with a low rate of false positives. The Medium urgency class also performed better than in previous models, with a precision of 0.80, though the recall dropped to 0.57, indicating that some medium urgency documents were not detected.

Technology Acceptance Model (TAM) Survey Results

Table 6. TAM Survey Results

CATEGORY	STRONGLY AGREE	AGREE	NEUTRAL	DISAGREE	STRONGLY DISAGREE
Usefulness	30	0	0	0	0
Ease of Use	25	5	0	0	0
Behavioural Intention	30	0	0	0	0

The Table 6 presents the distribution of user responses across three key categories: Usefulness, Ease of Use, and Behavioural Intention, using a standard Likert scale. The data reveals that most participants expressed strong agreement regarding the system's overall usefulness, its intuitive and user-friendly interface, and their intention to continue using it in the future. These results suggest a generally positive reception toward the system among users.

The survey shows strong user agreement on the system's usefulness, ease of use, and intention to continue using it.

Table 7. Descriptive Statistics of Perceived Usefulness of SDUPS

CRITERIA	MEAN	MEDIAN	MODE	STD DEV	VARIANCE
Using SDUPS improves my efficiency in managing documents.	5.0	5	5	0.0	0.0
SDUPS enables me to accomplish document-related tasks quickly.	5.0	5	5	0.0	0.0
SDUPS enhances my effectiveness in processing urgent documents.	5.0	5	5	0.0	0.0
SDUPS makes it easier to track and retrieve documents.	5.0	5	5	0.0	0.0
SDUPS is useful for my work in the SGOD office.	5.0	5	5	0.0	0.0
SDUPS helps reduce errors in document handling.	5.0	5	5	0.0	0.0

The Table 7 above shows survey results on SDUPS, with all criteria scoring a mean, median, and mode of 5.0. This indicates strong agreement that SDUPS improves efficiency, effectiveness, and error reduction in document management. The standard deviation and variance of 0.0 suggest uniform responses, with all participants rating it positively.

Table 8. Descriptive Statistics for Ease of Use of SDUPS

CRITERIA	MEAN	MEDIAN	MODE	STD DEV	VARIANCE
1. Learning to operate SDUPS was easy for me.	4.83	5	5	0.38	0.14
2. I find SDUPS easy to use.	4.83	5	5	0.38	0.14
3. The features of SDUPS are clear and understandable.	4.83	5	5	0.38	0.14
4. Interacting with SDUPS does not require a lot of mental effort.	4.83	5	5	0.38	0.14
5. I can use SDUPS without needing to consult the user manual or support.	4.83	5	5	0.38	0.14
6. It is easy to become skillful at using SDUPS.	4.83	5	5	0.38	0.14

Table 8 shows that users rated SDUPS highly regarding ease of use, with all criteria having a mean of 4.83, a median and a mode of 5. This indicates that most users agree the system is user-friendly and easy to learn. The low standard deviation (0.38) and variance (0.14) suggest consistent and favorable responses.

The survey results demonstrate that the system is highly effective. The unanimous strong agreement on usefulness highlights the system's significant impact on improving document management and processing efficiency. The strong agreement on ease of use, with a few respondents agreeing, suggests that the system is generally easy to learn and operate.

The mean rating for usefulness is 5.0, which is significantly higher than a neutral rating of 3 (p-value < 0.01). This indicates that respondents unanimously find the system highly useful.
The mean rating for ease of use is 4.83, which is also significantly higher than a neutral rating of 3 (p-value < 0.01). This suggests that respondents generally find the system very easy to use, with only minor variations.

The statistical analysis confirms that the system is highly effective. Both the usefulness and ease of use ratings are significantly higher than neutral, indicating strong positive feedback from the respondents. This demonstrates that the system is well-received and effective in improving document management and processing efficiency.

The survey results indicate a highly favorable response towards the system's usefulness and ease of use. The unanimous strong agreement on usefulness highlights the system's significant impact on improving document management and processing efficiency. The strong agreement on ease of use, with a few respondents agreeing, suggests that the system is generally easy to learn and operate, though there may be minor areas for improvement to achieve complete user satisfaction.

Table 9. One-Sample T-Test Results

CATEGORY	MEAN	STANDARD DEVIATION	T-STATISTIC	P-VALUE
Usefulness	5.0	0.0	∞	0.0
Ease of Use	4.83	0.37	26.49	7.16e-22

Table9 shows the statistical analysis of the TAM survey results and the model testing results demonstrate that the Smart Document Urgency Processing System is highly effective. The system is well-received by users, both in terms of its usefulness and ease of use. The combined approach of using SpaCY for feature extraction and ZSL for urgency scoring provides the best overall performance for urgency classification. Future work should focus on addressing the challenges in accurately classifying 'Low' urgency cases and exploring additional features to enhance the system's performance.

V. CONCLUSIONS AND RECOMMENDATIONS

Summary

The study evaluated the effectiveness of the Smart Document Urgency Processing System through a Technology Acceptance Model (TAM) survey and various model testing methods. The TAM survey results indicated that all 30 respondents strongly agreed on the system's usefulness, highlighting its significant impact on improving document management and processing efficiency. For ease of use, the majority of respondents (25 out of 30) strongly agreed, while 5 respondents agreed, suggesting that the system is generally user-friendly and easy to operate. The model testing results revealed that the Zero-Shot Learning (ZSL) model showed reasonable performance for the 'High' urgency category but struggled with 'Low' urgency classifications. The supervised training model yielded 100% recall for the 'High' urgency category but failed to predict 'Low' and 'Medium' urgency cases. The meta-classifier made slight improvements by incorporating additional features, yet the 'Low' urgency class remained underserved. Spacy, used for extracting due dates and document types, significantly improved the precision and recall, providing a more accurate classification. The combined approach (spacy + ZSL) demonstrated the highest performance metrics, indicating that combining the strengths of both models results in a more robust and reliable urgency classification system.

Conclusions

Based on the objectives and findings of the study, it can be concluded that the Smart Document Urgency Processing System is highly effective in improving document management and processing efficiency, as evidenced by the unanimous positive feedback on its usefulness. The system is generally user-friendly, with most respondents finding it easy to learn and operate. The combined approach of using spacy for feature extraction and ZSL for urgency scoring provides the best overall performance for urgency classification. Despite the improvements, the system still faces challenges in accurately classifying 'Low' urgency cases, indicating a need for further refinement and additional features.

Recommendations

To further improve the system, it is recommended that future research addresses the challenges associated with accurately classifying 'Low' urgency cases. This may involve the collection of additional labeled data, application of resampling techniques, or incorporation of features that better capture subtle urgency indicators. Continuous refinement of the system through user feedback and performance evaluation is essential. Moreover, the integration of advanced machine learning methods and expansion of the training dataset can significantly enhance the system's accuracy and reliability. Providing adequate user training and support will facilitate effective system utilization, while integration with existing document management systems can streamline workflows and improve operational efficiency. These recommendations aim to support the system’s ongoing development and ensure its long-term effectiveness.

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