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Original Article

A Review of AI-Enhanced Document Intake Systems Using OCR for Auto and Property Insurance Applications

Srinivas Dadi[1], Subhojit Ghosh[2]
[1,2]Independent Researcher.

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Abstract *- The algorithms of AI and the use of Optical Character Recognition (OCR) are redefining the automation of auto and property insurance, meaning that the unstructured and rather complex data can be shuffled around. The article cogitates on the processes of document classification, data extraction, and claims management using AI technologies, i.e., Machine Learning (ML), Natural Language Processing (NLP), and Robotic Process Automation (RPA). These systems improve the accuracy of operations, risk assessment, and fraud identification, and reduce the time spent on manual interaction and paper processing by automating volume and processing analysis. Moreover, AI-assisted OCR models are used to facilitate intelligent decisions, workflow, and insurance process compliance. The other aspect that is discussed in the research is a literature review of comparative OCR and its use in multilingual and handwriting text processing, which has led to the development of document intelligence in insurance. By default, AI-enabled OCR systems represent a significant advancement in automation of smart, data-driven and scalable document management in the insurance industry.*

Keywords *- Artificial Intelligence (AI), Optical Character Recognition (OCR), Intelligent Document Processing (IDP), Auto Insurance, Property Insurance, Machine Learning (ML).*

1. Introduction

The insurance industry has never stopped relying on extensive paperwork in underwriting, claims, and policy management. Manual handling of documents has become less efficient, more prone to errors, and increasingly time-consuming due to the explosive increase in the number and complexity of unstructured documents, such as claim forms, repair bills, property valuations, and ID proofs [1]. The recent breakthroughs in AI and OCR technology have enabled the automation of document handling, thereby greatly enhancing insurers' capacity to process information accurately and at a lower cost than before.

Optical character recognition (OCR) and text recognition applications are frequently employed in today's industry and research. This kind of application may save time and effort, which is where the true value resides [2]. Optical character recognition (OCR) is a computer-science technique that scans text from paper and converts the images into a format the computer can use, such as ASCII code. With an OCR system, one may use a word processor to edit a book or magazine article after it has been immediately fed into an electronic computer file [3]. Every OCR system has advanced software for image analysis and an optical scanner for text reading [4]. Most OCR systems employ a combination of hardware (specific circuit boards) and software to recognize characters, however, some cheap systems do it solely in software.

Intelligent Document Recognition (IDR) is an innovative technology that combines Automation of data extraction, categorization, and management from a variety of documents using artificial intelligence (AI), machine learning (ML), and optical character recognition (OCR) [5]. In contrast to conventional document processing techniques, which mostly depend on human data entry, IDR enables organizations to efficiently handle both structured and unstructured data with high accuracy. In modern business settings, invoice processing is a resource-consuming but important operation that needs to be conducted as organizations receive thousands of documents every day in multiple formats and layouts [6]. Nevertheless, with the technological advancements, a lot of enterprises remain attached to the manual data entry processes, which causes a great deal of operational inefficiency and higher costs of labour [7]. The current state of invoice processing in businesses indicates a multifaceted environment where the old-fashioned approach continues to struggle to meet the demands of contemporary businesses.

In the public sector, workflows and old systems are paper-based and cause inefficiencies, which cause time delays, mistakes, high risks of fraud and compliance issues [8][9]. In order to overcome these problems, AI-enhanced OCR and Intelligent Document Recognition (IDR) have been implemented more actively in the insurance, finance, and government industries, automating the data extraction process and increasing their accuracy and overall efficiency of operations [10]. The review is a detailed review of existing AI-based document intake models based on OCR in auto and property insurance. It examines their architectural components, model performance, and implementation challenges, while identifying key trends, research gaps, and opportunities for future development in intelligent insurance automation.

1.1. Structure of the Paper

The paper is structured as follows: Section II OCR Technologies describes algorithms and classification techniques, whereas Section III Integration of AI in Document Processing discusses ML, NLP, and RPA-based automation. Section IV Uses in Property Insurance concerns risk assessment and claims handling. Sections V Literature Review and Section VI - Conclusion and Future Work provide a summary of the findings and propose directions for further research.

2. Optical Character Recognition (OCR) Technologies

In insurance, at the very least, OCR is the basis for those systems that automatically take in documents, since it digitizes the unstructured claim documents, repair estimates and policy forms. This section provides a review of the development and the technical aspects that support OCR in AI-augmented insurance processes.

2.1. OCR in Document Processing and Archiving

The incorporation of OCR technology has greatly simplified the administration and preservation of documents. The document processing process involves converting paper documents such as legal and historical records into digital formats, especially when there is a large-scale preservation undertaking. Text can be machine-readable with the help of OCR, and thus it is easy to index, store and retrieve useful information [11]. Institutions and organizations can easily organize vast archives, which allows them to access the historical records and critical paperwork.

2.2. OCR in Data Extraction and Analysis

Unstructured data can pose a major issue to businesses and organisations in the modern data-driven world. The solution to this problem is the OCR technology that used to automate the task of data extraction in documents that are rich in text, including invoices, receipts and forms. OCR makes the data processing processes easier since it removes the possibility of re-typing or re-processing information to facilitate decision-making, which is more efficient and informed. This capacity to retrieve and process information is particularly helpful to those sectors that deal with large volumes of unstructured written information.

2.3. OCR for Text Recognition in Images and Videos

Text recognition in video and images has become a critical use of the OCR technology. Using OCR algorithms, it is possible to extract textual information in a broad variety of visual mediums by viewing images and video frames. This feature is practically applicable in various applications, e.g., license plate recognition (ALPR), reading subtitles in videos, and recognizing texts in streetlights and billboards. Through the text recognition capability of OCR in the visual media, there is an opportunity to automate and improve tasks dependent on text information.

2.4. OCR in Language Translation and Localization

The possibility of combining OCR with the technology of language translation opens the possibility of international communication and localisation of the content. OCR is effective when the scanned text is in a foreign language: it converts the text to a machine-readable form that can be translated using translation algorithms. Consequently, the language barriers are minimized, and the businesses and individuals more efficient in processing foreign-language content. This assimilation encourages cross-cultural communication and lays the groundwork for more inclusive interactions.

2.5. OCR in Accessibility for the Visually Impaired

Accessibility of people with visual limitations through OCR is one of the most influential uses. OCR translates printed text into a digital format, and this allows screen readers and other assistive equipment to read it aloud to people with poor vision. The breakthrough is equivalent to the increased accessibility of information books, articles, and other printed materials; this would allow individuals with visual deficiencies to become independent and more knowledgeable.

2.5.1. Evolution of OCR: From Rule-Based to AI-Powered Systems

The OCR technology based on AI has reached a high level, yet there are still problems with the recognition of complex scripts and handwriting. References to the past research indicate that OCR skills have continued to increase, and in ultra-new AI features, particularly in the newest DL packages [12]. Nonetheless, OCR generation continues to be constrained in its ability to identify low-resolution or scanned text, and that of handwritten comments, which are aligned with a standardized writing scheme. These difficult scenarios underscore the presence of the superior-quality device mastering models that should be able to intellectualize the context and adopt advanced pre-processing options. The results apply to business, library, and other administrative units that aim at complete digital transformation [13]. The possibility of transforming the physical information into digital formats is useful in promoting the accessibility of data, decreasing the amount of labour involved in manual work, and improving archives. The future research should centre on the improvement of contextual knowledge in AI-based OCR models and on reducing the error rates in tricky text cases. Further OCR training procedures, as well as the introduction of reinforcement learning and feedback of both present-day and consumer use, would also be able to improve OCR accuracy and adaptability.

2.5.2. Optical Character Recognition (OCR) Algorithm

A number of document types, such as scanned paper, PDF files, and digital camera images, may be converted into editable, searchable text via a process called optical character recognition (OCR). Characters from printed or handwritten text are extracted using OCR techniques, which allow computers to process and interpret data for automated processing [14]. Computers face a challenging task: scanned documents are converted into pixelated image files that must be located, detected, and identified to translate visual data into text, whereas humans can readily recognize patterns, typefaces, and styles. After being transformed into a machine-readable format, this material may be sorted into spreadsheets, used to produce reports and charts, and examined for trends, supporting a variety of applications as seen in Figure 1. A text editor cannot be used to edit, search, or count the words included in an image file. Nevertheless, OCR can turn the picture into a text document, keeping the text editable.

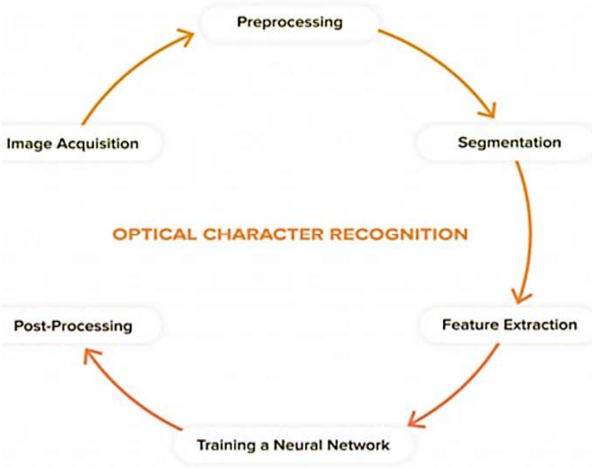

Fig 1: OCR Algorithm Flow

2.5.3. Recognition and Classification Techniques

Neural Networks (NNs):

A computing architecture made up of a massively parallel network of adaptable neural processors is called a neural network (NN). Its parallel nature may allow it to do computations faster than conventional approaches. Because it is adaptive, it can learn the characteristics of the input signal and adapt to data changes [15]. An NN has a large number of nodes. One node's output is sent to another, and the intricate relationships between all the nodes ultimately determine the outcome. In spite of the different underlying assumptions, it is shown that most NN designs are similar to statistical pattern recognition methods. In CR systems, the two most commonly used NNs are Korhonen's self-organizing map (SOM) for feedback networks and the multilayer perceptron of feedforward networks.

Optimum statistical classifiers:

Principal Component Analysis (PCA), Support Vector Machines, and Kernel Principal Component Analysis (KPCA) are the three most significant kernel techniques. SVMs are a subclass of supervised learning techniques that are employed in classification. Data for a classification job is often separated into test and training sets. A model that forecasts the desired values of the test data is what SVM aims to achieve. There are several varieties of kernel functions for SVMs, including sigmoid, linear, polynomial, and Gaussian Radial Basis Function (RBF).

3. Integration of AI in Document Processing in Insurance

AI-driven Intelligent Document Processing (IDP) streamlines document operations by combining robotic process automation (RPA), optical character recognition (OCR), natural language processing (NLP), and ML [16][17]. By automating categorization, extracting insights, converting paper documents into digital formats, and doing away with manual involvement, these technologies greatly increase productivity.

Efficiency Gains of AI-Driven IDP vs. Traditional Processing:

Claims Processing Time was reduced from 4-6 weeks to 24-48 hours (80% faster).

- Document Accuracy improved from 75% to 99.8% (33% increase).
- Compliance Review Time decreased from 2-4 months to 2 weeks (85% reduction).
- Fraud Detection Rate enhanced with AI-driven real-time alerts, detecting 50% more fraud before settlement.

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- Fraud Detection Rate enhanced with AI-driven real-time alerts, detecting 50% more fraud before settlement.
- Processing Claims the duration was shortened from 4-6 weeks to 24-48 hours, which is 80% quicker.
- The document accuracy increased by 33%, from 75% to 99.8%.
- Review of Compliance Time was cut by 85%, from 2-4 months to 2 weeks.
- AI-driven real-time notifications increased the fraud detection rate by 50% before settlement.

Businesses may save billions of dollars and boost customer satisfaction by implementing AI-powered IDP to improve compliance, cut down on fraud risks, and minimize inefficiencies.

3.1. Working of OCR With Machine Learning

To briefly explain this, Google Translate employs a procedure that is comparable to that of other image recognition engines. The initial task for the app is to identify the letters that are visible in the camera and separate them from any background visual stimulus. In order to finally distinguish letters from non-letters and detect individual letters, it uses a neural network to train the algorithm to recognize and identify patterns of pixel clusters and colours [18]. The translated text then shows in the camera view, where no untranslated text would be visible, when the Google Translate software has finally shown the translated letters over the original characters. Although the Google Translate app shows how optical character recognition may be used in many practical contexts, it currently only works with printed text and images and is not very effective with handwritten text. However, an AI that can read handwritten papers was created by a start-up named Omni: us using ML [19]. They provide devices that can process digital documents by extracting handwritten data from paper documents, and they target the banking and insurance industries with their services.

3.2. Al-Driven Intelligent Document Processing (IDP)

AI-driven Intelligent Document Processing (IDP) is a revolution rather than a simple improvement [20]. IDP can be used to automate the processing of large volumes of documentation within a government using ML, natural language processing (NLP), and robotic process automation (RPA). Al is able to extract key data, verify information, categorize records, and raise red flags on anomalies in real time, shortening processing time by more than 70% and reducing the occurrence of human errors.

States across the globe are starting to understand the strength of AI-based document automation (IDP). Whether by simplifying tax audit processes, speeding up benefit claims, or by making sure the regulatory environment is met, IDP can make governance smarter, faster and more secure. The paper discusses the way AI-based IDP transforms the nature of the work of the public administration, the most important technologies that contribute to this transformation, and the practical dimension of automation in the functioning of the government. Table I displays the Impacts of manual in the government.

Table 1: Impact of Manual vs. AI-Driven Document Processing in Government

Metric	Manual Processing	AI-Driven Processing	IDP Efficiency (%)
Document Processing Time (Days)	30–90	1–3	95% Faster
Human Error Rate (%)	15–25	<2	90% Reduction
Fraud Detection Rate (%)	50–60	95	58% Increase
Compliance Accuracy (%)	75	99.5	33% Improvement

3.3. Document Processing with Natural Language Processing

The importance of Natural Language Processing (NLP) in the automation of claims documentation is paramount because it is a time-consuming process. The unstructured data that is usually found in claim documents, such as police reports, customer statements, and invoices, should be analyzed and categorized [21]. Relevant information, including incident data, claim counts, and policyholder data, can be extracted with high accuracy using NLP algorithms. This automation saves time and effort because it removes manual data entry, minimize errors minimization and enhances the claims adjudication [22].

Table II below provides a comparison of the performance metrics of the traditional manual document processing and the AI-based NLP systems. The table indicates that, not only are the processing speed, errors reduced and cost-efficiency increased with NLP, but also to a significant extent.

Table 2: Performance Comparison: Traditional vs. AI-Based Document Processing in Claims Management

Metric	Traditional Processing	AI-Based NLP Processing
Average Processing Time	3–5 days	1–2 hours
Error Rate	10–15%	<2%
Operational Cost per Document	$15–$20	$3–$5

4. Applications in Property Insurance

The policy and claims paper processing can be automated and simplified using AI-enhanced document intake systems powered by OCR technologies [23]. These systems convert inspection reports, policy forms and claims submissions (handwritten or scanned) into structured digital data, which can be more easily retrieved and analyzed. It is also possible that insurers reduce the human factor and improve their decision-making by accurately deriving relevant data in property records, invoices, and damage estimates, combining OCR with AI models, including computer vision and natural language processing (NLP). The AI models also help in comparing claim information to policy data to identify irregularities using historical data and geographic data to evaluate risk. Such systems have been especially useful when disasters such as earthquakes or floods take place since they allow triage of huge claim papers to take place within a relatively short period of time, which results in settlement within a relatively short time [24]. AI-based OCR systems, when used in conjunction, enhance both the efficiency of operations and decrease the time required to process information, as well as provide the insurers and policyholders in the property insurance sector with more accurate, comprehensible information.

4.1. Policy Document Digitization and Classification

The classification of documents represents a significant activity that motivates different document image processing pipelines, including text recognition, information extraction, and document retrieval [25]. The paper processing system not only improves the overall efficiency but also saves time and gives an opportunity to perform numerous tasks, with the primary stage as sorting documents into specific categories. In literature, there are three major methods of document image classification, namely: three methods. The former type of techniques is founded on the design and arrangement of document images. This is a time-consuming process of plucking the key points of the documents and integrating them into the classification. The second approach is to come up with local or global descriptions of the images. These descriptors are geared toward classifying papers. It is a lengthy process that involves local and global extraction of features. The third technique involves the utilization of a CNN to automatically identify document image characteristics and classify them.

4.2. Automated Claims Handling for Property Damage

The multi-layered architecture of the technology-driven claims processing system is designed to integrate smoothly and make it scalable and efficient. The initial layer, or the first point of entry, is the Claims Submission [26]. Policyholders can file claims using chatbots, mobile apps, or online portals over this layer. Next, the information on the claim document is retrieved using AI technologies driven by OCR and NLP [27]. The trained AI/ML models are then included in the Claims Triage & Risk Assessment (AI & ML Layer). Each claim is rated for risk by the AI algorithms. Claims deemed risky are marked for human review. The low-risk claims are forwarded to automated adjudication.

This is preceded by Claims Adjudication and Decision Making (Business Rules) Layer. The business rule engine applies payout constraints, verifies policy authenticity, and assesses policyholder eligibility. Claims are automatically accepted, denied, or placed on hold. Blockchain checks policyholder documentation, and the Fraud Detection and Verification (Blockchain and AI Layer) compares claims with prior instances of identical fraud. The authorized claims are automatically subject to the payout in the Payout and Compliance Checks (Data and Security Layer) [28].Compliance engines ensure compliance with the GDPR, HIPAA, and NAIC regulations. The final architecture layer is the Continuous Learning and Performance Monitoring one, AI models are retrained according to the new fraud patterns and claims. The Performance dashboards observe different KPIs and metrics.

4.3. Risk Assessment Using AI-Processed Documents

The data gathered with the help of OCR and AI allows insurers to consider the risk of property and car insurance because they have access to more specific risk assessments on the basis of AI-processed documents [29]. To identify possible hazards, such as structural weaknesses, previous damage, or fraud, AI models analyze reports on inspections, maintenance logs, claim histories, and policy paperwork. Combining ML algorithms and Natural Language Processing (NLP) readings with geographical and sensor data can improve context comprehension by analyzing text for subtle indications of hazard. Predictive analytics are also useful in underwriting decisions to predict the chances of claims, and the extent of financial exposure [30]. Risk appraisal, which is automated, can decrease the human element, improve the uniformity of decisions, and offer dynamic risk scoring, which further leads to the effectiveness and accuracy of insurance operations. It is made possible through AI-processed document systems.

4.4. OCR Applications in Auto Insurance

The development of OCR and AI has been a blessing to automate document processing in auto insurance, which allows extracting and validating the main information related to vehicle-related documents in a short period of time: driver's license, registration, repair bill, and an accident report. Through these processes, the systems automatically acquire information, including Vehicle Identification Numbers (VINs), damage estimates, and policy information, thereby speeding up First Notice of Loss (FNOL) processing and automating claims adjudication [31]. The use of AI-based optical character recognition (OCR) technology has resulted in the reduction of human labor in data input and at the same time, it has helped to prevent fraud by checking the occurrence of the same data in more than one place, and to claim precision which in turn has led to the flow of operations and to a major uplift in the more customers friendly experience of motor insurance.

5. Literature Review

The present literature Summary focuses on developments in AI-assisted OCR and automation, with particular attention to regulatory, technical, and linguistic issues. The general studies prove enhanced accuracy, efficiency, and applicability of the various fields and propose adaptive regulation, hybrid-modelling, and interdisciplinary ways of working together in the future to build an AI-driven document processing system.

Naidu and Krishnan (2025) AI advancements are outpaced by rules, which leaves open questions about legal accountability for AI and user control over AI-generated conclusions and results in court cases. The paper outlines directions in the future of XAI for legal reasons, the application of federated learning to privacy concerns, and the necessity of promoting adaptive regulation. The analysis concludes by recommending that, in order to provide the optimal solutions for deploying AI, Legal Subject Matter Experts should work in conjunction with legal informatics specialists, ethicists, and legislators [32].

Afrin et al. (2025) The concept of intelligent automation driven by AI and based on the complementary use of AI and robotic process automation (RPA) to improve business and organizational operations in a variety of industries. RPA allows for the automation of repetitive, rules-driven processes, freeing up human workers to work on more creative tasks. Along with AI, RPA systems may be trained to comprehend data, identify patterns, classify information, and make predictions, which significantly improves accuracy and efficiency [33].

Mishra et al. (2024) a detailed comparison between the traditional approaches to the realization of Optical Character Recognition (OCR) systems and more modern and faster DL models than the one described above, including Transformers, BERT, and Bi-LSTM. OCR is a very vital method of converting print or handwritten text into electronics form to be utilized in text analysis and making digital forms of documents. The paper aids in realizing the pros and cons of both strategies, thus clarifying the functionality of the approaches on a real-life example. The new paradigm of information search takes advantage of semantic search with the help of bidirectional LSTMs and with the help of deep neural networks to understand the peculiarities of the textual analysis beyond the application of keywords in the information search [34].

Zhang et al.(2023) The recognition impact of OCR based on AI algorithms involves the classification and analysis of different AI algorithms used to analyze OCR. First, a summary of OCR's characteristics and operation using artificial neural networks is given. Second, despite the fact that ML-based OCR has better recognition effects and higher recognition accuracy, this article concludes that the algorithms currently in use for this kind of OCR are still in their infancy, with limited generalization and fixed recognition errors. Finally, a number of the most recent algorithms, including DL and pattern recognition algorithms, are examined in this work [35].

Srivastava et al. (2022). Optical Character recognition is one of the most prominent study topics nowadays. Many studies are being done on the identification of characters in many languages. English and Devanagari in India are the two most common of these languages. In English, a great deal of study has already been done. There is no study on the usage of Devanagari in more than 120 regional languages. Both handwritten and printed manuscripts can have their characters recognized. OCR systems are currently unable to reliably distinguish characters in Indian and other languages due to differences in script, quality, size, font, and style [36].

Zhou et al. (2021), the most popular approaches include three-dimensional modelling, segmentation, feature detection, and identification. Lighting modules, production systems, sensor modules, CV algorithms, decision-making modules, and actuators are all part of the recommended system structure for CV in a manufacturing environment. Then, applications of CV are examined in the production process, inspection and quality control, planning and scheduling, modelling and simulation, product design, assembly, transportation, and disassembly. Implementing algorithms, preparing data, labelling data, and benchmarking are among the difficulties [37].

A comparative summary of the recent literature on AI-enhanced OCR advancements, methods, fundamentals, research findings, issues and future prospects in relation to document intake systems in auto and property insurance is found in Table III

Table 3: Summary of a Study on AI-Enhanced Document Intake Systems Using OCR for Auto and Property Insurance Applications

Author	Study On	Approach	Key Findings	Challenges	Future Directions
Naidu and Krishnan (2025)	Legal and regulatory implications of AI innovations	Analytical review of AI regulations and governance frameworks	Found that AI advancements outpace regulatory developments, creating ambiguity in legal responsibility and user control	Lack of adaptive regulation and unclear accountability for AI-generated outcomes	Development of Explainable AI (XAI) for legal purposes, federated learning for privacy, and collaboration among legal, ethical, and policy experts
Afrin et al. (2025)	Intelligent automation using AI and Robotic Process Automation (RPA)	Integration of AI with RPA for process automation	Demonstrated that AI-enhanced RPA improves accuracy, efficiency, and productivity across industries	Integration complexity and dependency on data quality	Expansion of AI-RPA synergy for large-scale enterprise automation
Mishra et al. (2024)	Comparative analysis of OCR techniques	Evaluation of traditional OCR, CNNs, Bi-LSTM, and Transformer-based models	Identified deep learning models (e.g., BERT, Bi-LSTM) as superior for semantic understanding and accuracy	Computational cost and limited dataset diversity	Enhancement of OCR through hybrid AI models and semantic search integration
Zhang et al. (2023)	AI-based OCR algorithms	Classification and review of ANN and ML-based OCR systems	Found deep learning-based OCR achieves higher accuracy and robustness compared to traditional models	Limited generalization and fixed recognition errors	Further optimization of deep learning OCR models for broader language and document types

Srivastava et al. (2022)	OCR for multilingual character recognition	Experimental analysis on English and Devanagari scripts	Highlighted limitations in recognizing complex and handwritten scripts in Indian languages	Variations in font, style, and low OCR reliability for regional scripts	Development of adaptive OCR models for multilingual and handwritten document recognition
Zhou et al. (2021)	Computer Vision (CV) in manufacturing and document analysis	Framework integrating CV modules for detection, recognition, and decision-making	Proposed a CV framework applicable to product lifecycle and automated inspection	Algorithm complexity, data preprocessing, and benchmark limitations	Improvement of CV algorithms for real-time industrial and document applications

6. Conclusion and Future Work

The technologies of AI and Optical Character Recognition (OCR) have substantially improved the efficiency of document processing, particularly in the auto and property insurance industries. Intelligent Document Processing (IDP) systems powered by AI have enhanced operational precision, reduced reliance on humans, and improved risk assessment by automating document classification, data extraction, and claims analysis. To make better judgments and streamline operations, robotic process automation (RPA), ML, and natural language processing (NLP) are utilized. Moreover, ML OCR also enables more accurate interpretation of irregularly written or multilingual text documents, which is why it is better able to detect fraud and manage compliance. Although they offer these benefits, implementing these systems poses significant problems, including the high cost of installation, limited compatibility with current infrastructure, and concerns about the privacy and security of the information. These restrictions emphasize the need to continually simplify AI-driven document processing systems to enable flexibility and reliability, while also ensuring ethical control.

To enhance trust and openness, in the future, more attention should be paid to the development of understandable, privacy-aware AI models. Allowing OCR to work with other document types, catalyzing federated learning, and encouraging collaboration among AI developers, insurers, and policymakers will ensure that intelligent automation of insurance document processing is long-term, unbiased, and safe.

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