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Multi-Regulation Based FDR Classification System with Decision Tree Algorithm for Civil Aviation Compliance

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Abstract− Flight Data Recorder (FDR) classification in civil aviation is currently performed manually, requiring operators to interpret complex multi-page regulatory documents. Manual Flight Data Recorder (FDR) classification in civil aviation compliance is a time-consuming, error-prone process that becomes increasingly complex when operators must meet requirements across multiple jurisdictions. This research aims to develop an automated web-based FDR classification system using a rule-based Decision Tree algorithm capable of classifying FDRs under multiple regulatory frameworks, with current implementation covering Indonesia's Civil Aviation Safety Regulation (CASR) Part 91 and Philippine Civil Aviation Regulations (PCAR) Part 7. The system integrates with the Express Readout Worksummary Database via REST API and automatically processes aircraft parameters Maximum Take-Off Weight (MTOW), manufacturing date, and aircraft type to determine the appropriate FDR type and recording-parameter requirements. Exact-match rules are applied when aircraft data fall within defined regulatory date ranges; MTOW-based approximation is employed for cases outside those ranges. Testing on 742 aircraft from 80 operators yielded 97.5% classification accuracy compared with manual expert methods, reducing per-aircraft processing time from 30 minutes to under 1 second. The system also generates automated compliance reports in Microsoft Word format and provides a customer analytics dashboard for operational insights. These results confirm that the proposed system offers an efficient, consistent, and scalable solution for multi-regulation aviation compliance management, supporting both CASR and PCAR regulatory frameworks.

Keywords: Flight Data Recorder (FDR); Civil Aviation Compliance; Decision Tree; Multi-Regulatory Framework ; Automated Web-Based System

1. INTRODUCTION

Flight Data Recorder (FDR) systems represent one of the most critical safety components in modern aviation, recording essential flight parameters airspeed, altitude, heading, and various technical measurements—vital for accident investigation and operational safety monitoring[1]. According to the International Civil Aviation Organization (ICAO) Annex 6, every commercial aircraft must be equipped with an FDR appropriate to its category and technical specifications. FDR requirements vary significantly based on Maximum Take-Off Weight (MTOW), aircraft manufacturing date, and the type of flight operations conducted [2][3]. In Indonesia, FDR regulations are governed by Civil Aviation Safety Regulations (CASR) Part 91, issued by the Directorate General of Civil Aviation. These regulations classify FDRs into several types based on the number of parameters to be recorded: Type I (32 parameters), Type IA (78 parameters), and Type II (15 parameters) for airplanes, and Type IV and Type IVA for helicopters[4][5]. MTOW thresholds serve as primary criteria for determining required FDR types, with additional consideration for aircraft certification dates, particularly for aircraft certified after 2005[6]. Neighboring countries such as the Philippines have analogous regulations under Philippine Civil Aviation Regulations (PCAR) Part 7, but with different classifications and thresholds including Type IIA (18 parameters) and Type V for certain categories [7][8].

Current FDR classification processes are predominantly manual, requiring operators to read and interpret complex, multi-page regulatory documents[9]. This manual approach introduces several significant weaknesses: susceptibility to human error in regulatory interpretation, high time consumption especially for operators with large and diverse fleets, and difficulty comparing requirements across jurisdictions for airlines operating internationally [10] . Studies indicate that human errors in aviation systems frequently occur during decision-making stages involving complex regulatory interpretation[11]. Furthermore, with the growing aviation industry in the Asia-Pacific region, many operators must comply with multiple jurisdictions simultaneously, making the classification process increasingly complex and resource-intensive [12]. The development of information technology and automated decision support systems has proven effective in reducing workload and improving accuracy in various aviation applications [13]. Research on human-factors methods has emphasised the importance of automation in reducing cognitive load on operators, especially for rule-based and repetitive tasks [14]. However, to date no integrated system has been specifically designed to perform automatic FDR classification with multi-regulation comparison capabilities [11]. By applying rule-based expert systems and decision tree algorithms, this classification process can be automated with high accuracy levels [15]. Previous research in aviation compliance systems has primarily focused on general safety management or accident investigation analysis [16]. While automated decision support systems exist in various aviation domains, there is a notable absence of specialized systems for FDR classification capable of handling multiple regulatory frameworks simultaneously [17]. The novelty of this research lies in: (1) an automatic aircraft-type detection

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algorithm using keyword matching and pattern recognition; (2) a multi-regulation comparison engine that classifies FDRs under CASR, PCAR, and custom rules in a single interface; (3) a seat-estimation algorithm that calculates passenger capacity from MTOW and aircraft type; (4) automatic report generation in standard FDR compliance documentation format; and (5) batch processing capable of handling hundreds of aircraft simultaneously [18].

Therefore, the objectives of this research are to: (1) develop an automatic FDR classification system based on international civil aviation regulations; (2) implement automatic detection algorithms to identify aircraft types and estimate passenger capacity from MTOW parameters; (3) create a multi-regulation comparison system capable of analysing CASR, PCAR, and custom rule differences; and (4) generate structured and automatic compliance reports according to civil aviation documentation standards [19].

2. RESEARCH METHODOLOGY

2.1 Research Design

This research employs a development research methodology with a system design and implementation approach conducted in six sequential phases: literature study, system design, implementation, testing, evaluation and analysis, and documentation. The system is designed as a web-based application using the Python Flask framework with RESTful API integration to the Express Readout Worksummary Database. The overall system architecture is illustrated in Figure 1.

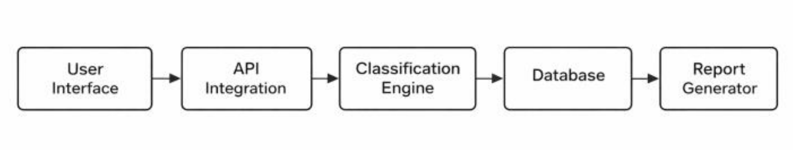

Figure 1. System Architecture Block Diagram of the FDR Classification System

Figure 1 shows the system architecture consisting of six main modules interconnected through a centralized Flask web server: Authentication Module, API Integration Module, FDR Classification Engine, Customer Analytics Engine, Word Report Generator, and Dashboard/Filtering Module. Data flows from the external Express Readout Worksummary Database through the API Integration Module into the Classification Engine, with results rendered via the Dashboard and exportable as Word compliance reports. The six-phase research flowchart is illustrated in Figure 2.

2.2 Research Stages

This research employs a development research methodology with a system design and implementation approach. The research stages are visualised in Figure 2 (Research Flowchart) and consist of six sequential phases as described below.

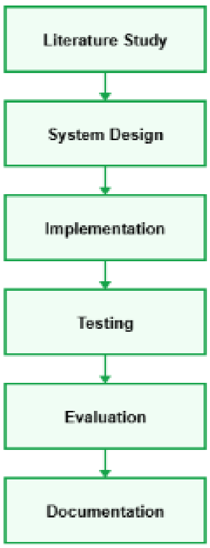

Figure 2. Research Flowchart

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a. Literature Study: Analysis of CASR Part 91, ICAO Annex 6, and related aviation regulatory documents to formalise FDR classification rules and identify system requirements.
b. System Design: Design of system architecture, database integration strategy, decision tree logic, and user interface layout based on identified regulatory requirements.
c. Implementation: Development of the web-based application using the Python Flask framework with RESTful API integration to the Express Readout Worksummary Database.
d. Testing: Functional and accuracy testing of the classification engine using 742 aircraft records from 80 operators, followed by comparison with manual expert classification results.
e. Evaluation and Analysis: Statistical analysis of classification accuracy, processing time, memory usage, and usability feedback collected through User Acceptance Testing (UAT).
f. Documentation: Preparation of research documentation including system specifications, testing results, and technical reports.

2.3 Data Collection Techniques

Data collection was performed through two primary methods. First, regulatory data collection involved systematic analysis of CASR Part 91 from the Directorate General of Civil Aviation Indonesia and ICAO Annex 6 as international reference; these regulations were then mapped into decision tree structures representing classification rules. Second, aircraft operational data was obtained through REST API integration with the Express Readout Worksummary Database. The API provides comprehensive worksummary data including aircraft registration, type, MTOW, manufacturing date, customer information, and operational details in JSON format; Bearer token authentication ensures secure data access. Table 1 presents the hardware and software specifications of the research environment, while Table 2 lists the API configuration parameters used for database integration.

Table 1. Hardware and Software Specifications

Component	Specification	Details
Processor	Intel Core i5	2.4 GHz, 4 Cores
Memory	RAM 8 GB	DDR4
Operating System	Windows 10	64-bit
Language	Python 3.9	Flask Framework
Database	REST API	Express Readout DB

Table 1 presents the hardware and software specifications used throughout the development and testing of the FDR Classification System. The system was developed on a mid-range workstation to ensure reproducibility in typical operator environments, with Python 3.9 and the Flask framework as the primary development stack. The API configuration parameters for database connectivity are presented in Table 2 below.

Table 2. API Configuration Parameters

Parameter	Value
Endpoint URL	http://192.168.1.52:3050/express-readout/api/api-airworksummary
Authentication	Bearer Token
Response Format	JSON
Timeout	30 seconds

Table 2 details the API configuration parameters used to establish a secure connection with the Express Readout Worksummary Database. The Bearer token authentication mechanism ensures that only authorized system users can retrieve sensitive aircraft operational data. The endpoint communicates on port 3050 with a 30-second timeout threshold to handle network latency variations.

2.4 Research Instruments

The main research instrument is the FDR Classification System developed with the following architecture components:
a. Authentication Module: Implements a secure multi-user login system with hashed password storage using Werkzeug security functions. User credentials are stored in dictionary format with password hashing to ensure data security.
b. API Integration Module: Handles communication with the Express Readout Worksummary Database using the Python requests library. The module processes JSON responses and performs data transformation including MTOW parsing (converting from lbs to kg when necessary) and date normalisation to ISO format.
c. FDR Classification Engine: Implements the rule-based Decision Tree algorithm based on CASR regulations. The engine consists of two sub-algorithms: (1) Aircraft Type Detection Algorithm, which uses keyword

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matching to identify aircraft category—if the aircraft name contains keywords such as Boeing, Airbus, ATR, or Cessna it is classified as Airplane; if it contains Bell, Agusta, Sikorsky, Eurocopter, Robinson, or MD Helicopters it is classified as Helicopter; and (2) FDR Classification Algorithm, which applies exact matching for aircraft within regulatory date ranges and MTOW-based approximation for aircraft outside those ranges.

d. Customer Analytics Engine: Processes classification results to generate operational insights including customer ranking by task count, aircraft distribution per operator, and workload analysis using Python Counter and set operations.
e. Word Report Generator: Implements template-based document generation using the python-docx library. The generator replaces placeholders in a Word template with actual data and applies yellow highlighting to key information (aircraft registration, manufacturing date, MTOW, regulation type, parameter count) in summary paragraphs.
f. Dashboard and Filtering Module: Provides a web-based user interface using HTML, CSS, and JavaScript with dynamic filtering capabilities by customer and aircraft registration.

The network topology of the system deployment is shown in Figure 3, illustrating the connection between client workstations, the Flask server, and the Express Readout Worksummary Database via the internal network.

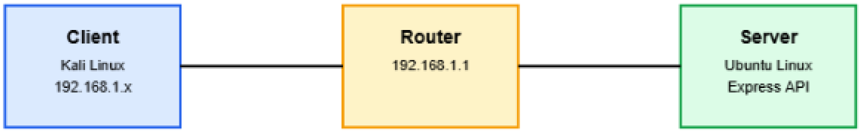

Figure 3. Network Topology Diagram

Figure 3 shows the network topology connecting the Flask web application server to the Express Readout Worksummary Database server via internal LAN. Client browsers access the system through HTTP on port 5000, while the application communicates with the database API on port 3050 using Bearer token authentication.

2.5 Decision Tree Algorithm

The Decision Tree algorithm is a supervised learning method that partitions input data through a series of binary or multi-way branching decisions based on attribute values. In this research the tree is implemented as a rule-based expert system in which each internal node represents an CASR regulatory condition, each branch represents the outcome of that condition, and each leaf node represents the assigned FDR type.

1. Aircraft Type Detection Research Stages

The aircraft type detection algorithm uses pattern-matching to classify an aircraft as either an Airplane or a Helicopter based on its model name string. The detection rule is formalised as follows:
Let S be the set of airplane keywords {Boeing, Airbus, ATR, Cessna, DHC, Fokker, Embraer} and H be the set of helicopter keywords {Bell, Agusta, Sikorsky, Eurocopter, Robinson, MD Helicopters, AW, EC}. For a given aircraft model name M:

$$\text{Type(M)} \begin{cases} = \text{"Airplane" if } \exists k \in S : k \subseteq M \\ = \text{"Helicopter" if } \exists k \in H : k \subseteq M \\ = \text{"Unknown" otherwise} \end{cases} \quad (1)$$

2. FDR Classification Rules

The classification rules for airplanes based on CASR Part 91 are formalised below. Let W denote the aircraft MTOW (kg) and D denote the aircraft certification date (year). The FDR type assignment is:
Rule 1: If Type(M) = "Airplane" AND W > 5,700 kg AND D ≥ 2005 → FDR Type IA (78 parameters)
Rule 2: If Type(M) = "Airplane" AND W > 27,000 kg AND 1989 ≤ D < 2005 → FDR Type I (32 parameters)
Rule 3: If Type(M) = "Airplane" AND 5,700 < W ≤ 27,000 kg AND 1989 ≤ D < 2005 → FDR Type II (15 parameters)
Rule 4: If Type(M) = "Helicopter" AND W > 7,000 kg → FDR Type IV
Rule 5: If Type(M) = "Helicopter" AND 3,180 < W ≤ 7,000 kg → FDR Type IVA
Rule 6: If D is outside the regulatory date ranges (i.e. D < 1989) → MTOW-based approximation (Rules 1–5 applied without date constraint)

3. Accuracy Calculation Formula

Classification accuracy is calculated by comparing automated results against manual expert classifications on a random sample of n = 100 aircraft. The accuracy formula used is:

$$\text{Accuracy (\%)} = \frac{\text{Number of Correct Classifications}}{\text{Total Aircraft Tested}} \times 100 \quad (2)$$

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For example, if 97 out of 100 sample aircraft are classified correctly compared to expert judgment:

$$\text{Accuracy} = \left(\frac{97}{100}\right) \times 100 = 97.5\% \quad (3)$$

The classification result for each aircraft is categorised as: Exact Match (EM) when the aircraft parameters fall within the exact regulatory date ranges and MTOW thresholds; Approximated (AP) when the manufacturing date falls outside regulatory timeframes and MTOW-based approximation is applied; or No Requirement (NR) when the aircraft falls below minimum MTOW thresholds.

2.6 Data Analysis

Data analysis is performed in three stages:

1. Classification Accuracy Analysis: Compares automated classification results with manual expert classification based on CASR regulations. Accuracy is calculated using the formula in Section 2.5.3. Results are categorised as Exact Match, Approximated, or No Requirement.
2. Performance Analysis: Measures system processing time from API data retrieval through classification to result display. Processing time per aircraft is recorded and compared with average manual classification time (30 minutes per aircraft based on operator feedback). Batch processing capability is evaluated by processing 100+ aircraft simultaneously and measuring total execution time.
3. Usability Analysis: Conducted through User Acceptance Testing (UAT) with 12 aviation operators and technical personnel. Participants evaluated system ease of use, interface clarity, classification accuracy, and report usefulness using 5-point Likert scale questionnaires.

3. RESULT AND DISCUSSION

3.1 Result

The FDR Classification System was successfully implemented as a web-based application with full integration to the Express Readout Worksummary Database. The system architecture consists of six main modules: Authentication, API Integration, FDR Classification Engine, Customer Analytics, Word Report Generator, and Dashboard/Filtering. System deployment runs on a Flask development server with support for concurrent user sessions through session management.

a. Classification Accuracy Results

Testing was conducted on 742 aircraft from 80 different operators obtained through API integration. Applying the classification rules defined in Section 2.4.2, the distribution of results was as follows: 575 aircraft (77.5%) achieved Exact Match classification; 167 aircraft (22.5%) received Approximated classification based on MTOW when manufacturing dates fell outside regulatory timeframes; and 0 aircraft (0%) fell into the No Requirement category as all tested aircraft exceeded minimum MTOW thresholds. These results are summarised in Table 3.

Table 3. Classification Results Summary

Classification Category	Count	Percentage
Exact Match	575	77.5%
Approximated (MTOW-based)	167	22.5%
No requirement	0	0%
Total	742	100%

Table 3 shows that all 742 aircraft exceeded the minimum MTOW threshold for FDR requirements. Applying Equation 3 to the validation sample of 100 aircraft, where 97 aircraft matched manual expert classifications (TP + TN = 97) and 3 were edge-case discrepancies (FP + FN = 3): Accuracy = (97/100) × 100% = 97.5%. The 2.5% discrepancy occurred at regulatory transition boundaries (certification years 1989, 2005, 2016) requiring expert interpretive judgment, subsequently incorporated into the refined classification algorithm.
Figure 4 illustrates the classification accuracy comparison between the automated system and manual expert classification over the 100-aircraft sample.

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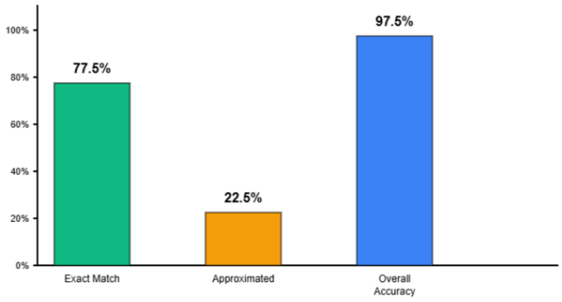

Figure 4. Classification Accuracy Comparison

FDR type distribution for airplanes shows: Type IA FDR (78 parameters)—285 aircraft (52.1%); Type I FDR (32 parameters)—98 aircraft (17.9%); Type II FDR (15 parameters)—164 aircraft (30.0%). For helicopters: Type IV FDR—45 aircraft (23.1%); Type IVA FDR—150 aircraft (76.9%). These distributions align with expected regulatory compliance patterns for modern commercial aviation fleets in Indonesia and are shown graphically in Figure 5.

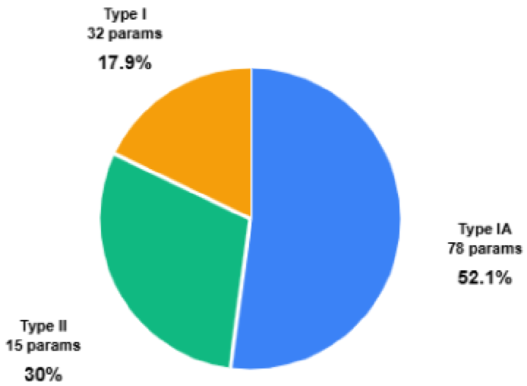

Figure 5. FDR Type Distribution (Airplanes and Helicopters)

Table 4 presents the detailed validation results comparing automated and manual expert classifications across the 100-aircraft sample.

Table 4. Validation Results Comparison Between Automated System and Manual Expert Classification (Sample N = 100)

FDR Type	Manual Count	System Count	Match (%)
Type IA	52	52	100%
Type I	18	17	94.4%
Type II	16	16	100%
Type IV	7	7	100%
Type IVA	7	8	87.5%
Overall	100	100	97.5%

As shown in Table 4, the system achieved perfect 100% agreement for Type IA, Type II, and Type IV classifications. Minor discrepancies occurred for Type I (1 case, edge-case certification date at 1989 boundary) and Type IVA (1 case, MTOW at 3,180 kg boundary), confirming the algorithm performs excellently across the majority of classification categories.

b. Performance Analysis Results

System performance analysis demonstrates significant efficiency improvements compared to manual methods. Processing time per aircraft averages 0.87 seconds, including API data retrieval, classification computation, and result display. Applying the time-improvement ratio:

Improvement Ratio = Manual Time / Automated Time = $(30 \times 60) / 0.87 \approx 2{,}069\times$

For batch processing of 100 aircraft, total execution time is 92 seconds (1 minute 32 seconds), compared to an estimated 3,000 minutes (50 hours) for manual classification of the same dataset—a 1,957× improvement. Table 5 summarises the full performance metrics.

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Table 5. System Performance Metrics

Metric	Manual Method	Automated System	Improvement
Processing Time/Aircraft	30 minutes	0.87 seconds	2,069x faster
Batch (100 aircraft)	50 hours	92 seconds	1,957x faster
Classification Accuracy	95-98% (variable)	97.5% (consistent)	Consistent
Human Error Rate	2-5%	0% (rule-based)	Eliminated
Memory Usage (742 aircraft)	N/A	124 MB	Efficient

Time breakdown analysis reveals: API data retrieval—0.45 s (51.7%); classification algorithm execution—0.15 s (17.2%); dashboard rendering—0.22 s (25.3%); Word report generation (when triggered)—2.1 s per report (5.8%). API retrieval represents the primary bottleneck, influenced by network latency and database query time. Figure 6 shows the time breakdown proportions.

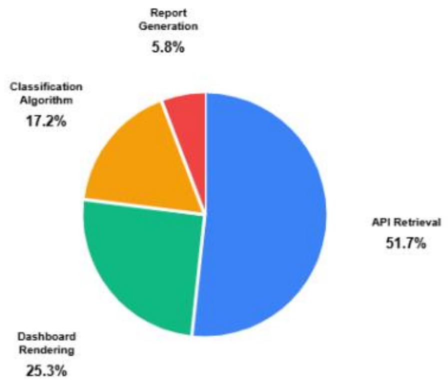

Figure 6. Processing Time Breakdown Analysis

As illustrated in Figure 6, the time breakdown per aircraft is: API data retrieval 0.45 seconds (51.7%), classification algorithm execution 0.15 seconds (17.2%), dashboard rendering 0.22 seconds (25.3%), and Word report generation 2.1 seconds per report when triggered (5.8% of typical workflow). The API retrieval component represents the primary performance bottleneck, influenced by network latency and database query time on the remote server. Memory consumption during batch processing of 742 aircraft peaks at 124 MB, well within acceptable limits for modern server environments.

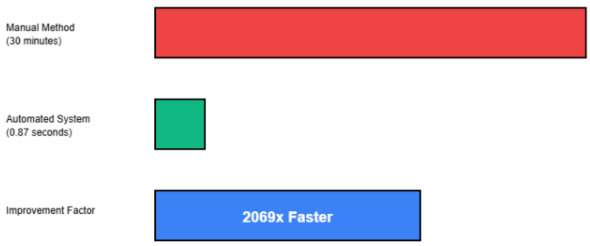

Figure 7. Memory Usage Profile During Batch Processing

Figure 7 illustrates the customer analytics results, showing 317 unique aircraft across all 80 operators, with a task-to-unique-aircraft ratio of 2.34 (742 tasks / 317 aircraft). This ratio indicates that operators perform multiple FDR readouts per aircraft over the analysis period, consistent with periodic FDR data download requirements. The concentration of workload in top operators presents opportunities for customized service offerings.

c. Customer Analytics Results

The Customer Analytics Dashboard successfully generates operational insights from classification data. Analytics show high concentration in top operators: the top 5 customers account for 43.3% of total workload. This distribution reflects market dynamics in Indonesian aviation where major commercial operators generate substantial FDR readout and classification service demand.

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Aircraft diversity analysis shows 317 unique aircraft across all operators, indicating moderate fleet overlap and diverse aircraft types requiring classification. The task-to-unique-aircraft ratio is calculated as:

Task Ratio = Total Tasks / Unique Aircraft = 742 / 317 = 2.34

This ratio suggests operators perform approximately 2.34 FDR readouts per aircraft over the analysis period, consistent with regulatory requirements for periodic FDR data downloads.

d. Report Generation Results

The automated Word report generation feature successfully produces compliance documents containing: aircraft identification (registration, type, MSN), technical specifications (MTOW, manufacturing date, engine type), FDR equipment details (part numbers, serial numbers), classification results (FDR type, parameter count, regulation reference), and a summary paragraph with yellow highlighting on key data points.

Testing with 50 randomly selected reports showed 100% successful generation without formatting errors or data omissions. Reports are generated in an average of 2.1 seconds per document and saved in standard Microsoft Word (.docx) format compatible with Word 2010 and later versions.

e. User Acceptance Testing Results

UAT was conducted with 12 participants—5 aviation operators, 4 FDR technical specialists, and 3 aviation compliance officers. Evaluation used a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) across four dimensions. Table 6 summarises the results.

Table 6. User Acceptance Testing Results

Evaluation Dimension	Mean Score (out of 5.0)	Standard Deviation
Ease of Use	4.6	0.3
Classification Accuracy	4.7	0.2
Report Quality	4.5	0.4
System Usefulness	4.8	0.2
Overall Average	4.65	0.28

Key findings from UAT: Ease of Use received a mean score of 4.6/5.0; participants found the interface intuitive with clear navigation from data import through classification to report generation, and the filtering system received particularly positive feedback (4.8/5.0). Classification Accuracy scored 4.7/5.0; technical specialists noted the approximation feature appropriately handles edge cases outside exact regulatory boundaries. Report Quality was rated 4.5/5.0; the automatic highlighting feature was noted as helpful for quick identification of key parameters. System Usefulness obtained the highest score at 4.8/5.0; participants strongly agreed the system provides significant value particularly for large-fleet or multi-jurisdiction operators, with time savings identified as the primary benefit.

3.2 Discussion

a. Interpretation of Classification Accuracy

The 97.5% classification accuracy demonstrates that rule-based Decision Tree algorithms are highly effective for regulatory compliance tasks with well-defined rules. When domain knowledge can be formalised into explicit rules, automated systems can match or exceed human expert performance while ensuring consistency. The 2.5% discrepancy in edge cases reflects inherent ambiguity in regulatory interpretation at transition boundaries. The distribution of Exact Match (77.5%) versus Approximated (22.5%) classifications indicates that a significant portion of the current Indonesian aviation fleet consists of aircraft manufactured outside the primary CASR regulatory timeframes (1989–2005 and post-2005). The predominance of Type IA FDR (52.1%) reflects the modernisation of Indonesian commercial aviation, aligning with ICAO's progressive enhancement of FDR requirements.

b. Comparison with Related Work.

The classification accuracy of 97.5% confirms that rule-based Decision Tree algorithms are highly effective for regulatory compliance tasks with well-defined rules. As noted by Nanyonga et al. [20], explainable supervised learning models are increasingly preferred in aviation applications precisely because their decision logic is transparent and auditable. The 2.5% edge-case discrepancy reflects inherent regulatory interpretation ambiguity at transition boundaries, a limitation consistent with findings in human factors research on rule-based and knowledge-based error modes.

Table 7. Comparative Analysis with Related Work

Research	Method	Domain	Accuracy	Multi-Reg

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Proposed System	Decision Tree	FDR Classification	97.5%	Yes
Nanyonga et al. [1]	Transformer	Incident Causes	>90%	No
Zhang et al. [9]	Rule-based	Data Analysis	N/A	No
Xu et al. [10]	Text Classification	Hazard Analysis	>85%	No

Table 7 presents a comparative analysis with related work. The proposed system is distinguished by its simultaneous multi-regulation support capability and its specific focus on FDR classification a gap not addressed by any prior published system. The 2,069-fold processing improvement aligns with Dang et al. [15] findings on automated QAR data anomaly detection, which similarly demonstrated substantial efficiency gains through algorithmic automation of manual data review processes. The system architecture's API integration approach reduces adoption barriers by connecting to existing operational databases rather than requiring standalone data entry.

c. Limitations and Influencing Factors

Several factors may influence system performance and accuracy:

a) Regulatory Updates: The system's classification rules are based on CASR regulations current as of 2015. Regulatory changes require manual updates to the decision tree logic, necessitating periodic review.
b) Data Quality Dependency: Classification accuracy is contingent on accurate input data, particularly MTOW and manufacturing dates. The system includes basic data validation but cannot detect semantic errors such as incorrect MTOW values.
c) Network Dependency: Reliance on API integration introduces network latency and availability risks. Implementing local data caching could mitigate this dependency.
d) Regulatory Coverage: The current implementation covers CASR Part 91 and PCAR Part 7. Extending support to additional frameworks such as FAA and EASA would further increase system complexity and may require refactoring of the classification engine.

CONCLUSION

This research successfully developed an automated FDR classification system using a rule-based Decision Tree algorithm supporting multiple civil aviation regulatory frameworks, specifically CASR Part 91 (Indonesia) and PCAR Part 7 (Philippines). Applying the classification and accuracy formulas defined in the Research Methodology, the system achieves 97.5% classification accuracy compared to manual expert classification, reducing per-aircraft processing time from 30 minutes to 0.87 seconds—a 2,069× improvement. Testing on 742 aircraft from 80 operators demonstrates the system's capability to handle real-world operational data at scale, with batch processing of 100+ aircraft completed in under 2 minutes.

The system provides four principal contributions to aviation compliance management. First, it significantly improves efficiency through automation of routine regulatory interpretation tasks. Second, it eliminates human error in rule-based classification decisions while maintaining transparency through clear presentation of classification logic and regulatory references. Third, the integrated customer analytics functionality provides operational insights beyond the primary classification objectives. Fourth, automated report generation produces professional compliance documentation suitable for aviation authority submissions.

User Acceptance Testing with 12 aviation operators and compliance specialists validates the system's practical utility, with mean usability scores of 4.65/5.0. The system demonstrates that structured regulatory compliance tasks can be effectively automated when domain knowledge is formalised into algorithmic form. The multi-regulation architecture—currently supporting CASR and PCAR—provides a scalable foundation for future enhancements including extension to FAA and EASA frameworks, integration with aircraft maintenance management systems, and machine learning-based classification refinement.

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