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Online Dispute Resolution: The Future of ADR in the Digital Age

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Abstract - This paper offers a hybrid ODR architecture meant to improve the conflict settlement process by merging machine learning techniques with automated mediation systems. The framework is ran through many simulations, during which its performance is compared to that of other ODR approaches currently in use. This method is novel since it combines automated mediation with human participation, hence producing a hybrid nature. It ensures optimal decision-making and helps to improve the quality of dispute resolutions. Over time, the system will change and adjust to become more efficient and powerful. To speed the training of machine learning models, the experiment is run on a cloud-based computing system employing Amazon Elastic Compute Cloud instances and GPU support. This method is evaluated in comparison to three other presently employed techniques: Traditional ODR Systems, AI-Powered ODR Systems and Hybrid ODR Systems.

Keywords - Online Dispute Resolution, Alternative Dispute Resolution, Machine Learning, Mediation, Technology Integration

I. Introduction

Online Dispute Resolution (ODR) in current digital technology era become a realistic option to solve the conflict resolutionissues. ODR systems let companies and individuals resolve issues using online tools, hence making the process more accessible, quicker, and more economical. ODR uses technology such artificial intelligence (AI), machine learning, and natural language processing (NLP) [1] to automate the process of conflict resolution and deliver tailored solutions for a range of various sorts of disputes [2]-[8].

This paper's major objective is to present a new hybrid alternative dispute resolution (ADR) system driven by AI to increase user happiness, resolution time, cost-efficiency and accuracy. Among the key goals are the following:

1. To evaluate the extent of the solution (for example, to determine whether both sides are satisfied with the outcome) and to collect feedback so that changes may be made moving forward.
2. The cross-performance indicator comparison reveals that the proposed ODR system's implementation has generated significant advantages. When compared to conventional approaches, the proposed approach was able to reduce the average time required for resolution by fifty percent, hence enhancing the level of efficiency.

II. Related Works

Recent research has largely concentrated on enhancing the performance of ODR systems as well as the user experience by means of more sophisticated artificial intelligence and machine learning models. Many studies show that adding emotional detection and sentiment analysis into ODR systems could improve consumer satisfaction. These technologies are able to better satisfy the emotional requirements of participants during the mediation process, therefore this. Results of a [9] study indicate that incorporating emotion detection into an ODR platform greatly increased user participation and system confidence. Furthermore, research is examining how deep learning algorithms could forecast the likelihood of successful dispute resolutions based on data from prior occurrences. This would enable more dynamic and flexible processing [10-12].

III. Proposed Method

By integrating machine learning algorithms with an automated mediation system, the proposed method simplifies online conflict settlement provided in figure 1. The approach comprises activities such as the following:

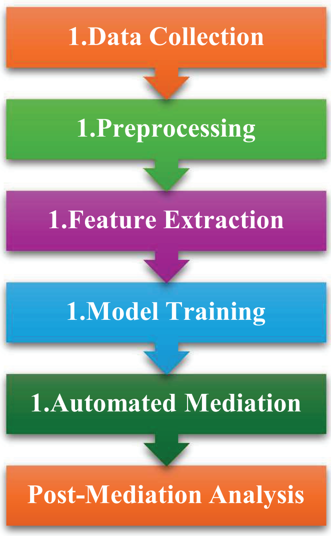

Fig. 1. PROPOSED FRAMEWORK

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A. Data Collection

The first stage in the proposed method is to collect data from ongoing contests of opinion taking place on an internet forum. This data includes the history of communication, different types of conflicts, participant demographics, and any other pertinent metadata. A wide range of data reflecting many different kinds of conflicts, such as employment, consumer, and contract disputes, for example, is acquired to ensure the model is trained in an efficient way.

Table I is one illustration of the information compiled from several war scenarios.

TABLE I: COLLECTED DATA

Dispute ID	Dispute Type	Participant 1 Age	Participant 2 Age	Communication Length	Resolution Status
1001	Contract	45	38	25	Resolved
1002	Consumer	29	32	15	Unresolved
1003	Employment	50	40	20	Resolved
1004	Property	34	28	30	Unresolved

The data covers the type of conflict, the players' demographics (age), the duration of communication, and the state of the resolution (resolved or unresolved). The next processing is based on this raw data.

B. Preprocessing

Preprocessing guarantees the purity and suitability for analysis of the collected data. Preprocessing is made up of:

- Handling Missing Data: Any missing dataset values are filled in using methods such mean imputation or row deletion. Examples of missing values are the participant's age or the length of the conversation.
- Normalization: Large numerical differences do not affect the performance of the model since the numerical values, such as the length of communication or age, are normalized to a similar scale, for example, 0 to 1.
- Categorical Encoding: This method converts non-numerical data, such as the types of disputes and the status of resolutions, into numerical values; for example, 0 indicates unresolved and 1 indicates resolved.

Table II depicts the likely appearance of the data post-processing.

C. Feature Extraction

The process of turning raw data into meaningful features that can be used to train machine learning models is called feature extraction. This method is sometimes referred to as feature extraction. This method extracts features from the conversation history using Natural Language Processing (NLP) technologies. Among the most vital components included in the text are:

- Sentiment Score: One studies the sentiment of every message to decide whether the communication is good, negative, or neutral.
- Keyword Frequency: Important words or phrases (such as "refund," "breach," and "contract") are extracted from the signals they contain to grasp the most vital aspects of the issue.
- Tone Analysis: Tone study is the technique of understanding the tone of a conversation to decide if it is formal, confrontational, or courteous.

The equation below shows how to calculate the sentiment score.

$$S = \frac{P - N}{P + N} \tag{1}$$

where:

Sis the sentiment score.

P is the number of positive words in the text.

N is the number of negative words in the text.

The sentiment score suggests if the interaction is generally good or bad, which could affect the strategy used to solve the issue. Table III lists the features drawn from the conflict communication data.

TABLE III: EXTRACTED FEATURES FROM COMMUNICATION

Dispute ID	Sentiment Score	Keyword Frequency (Refund)	Keyword Frequency (Breach)	Tone (Formal)
1001	0.20	2	0	Yes
1002	-0.50	1	1	No
1003	0.30	0	0	Yes
1004	-0.10	3	2	No

The sentiment score in this figure indicates the emotional tone of the messages; the keyword frequency columns monitor how often notable terms related to the conflict appear. The tone column, which shows whether or not the communication was written in a formal manner, determines the sort of the conflict.

Transformed into relevant qualities that may be fed into a machine learning model, the raw data enables the system predict possible conflict resolution techniques. The raw data evolves, hence these phases are finished.

D. Model Training

After the data has been preprocessed, the next step is to train a machine learning model using the same data. Using the characteristics acquired from previous conflict data, this work aims to educate the model to predict the most effective mediation approach. Supervised learning, in which the model is trained with labeled data (dispute outcomes labeled as either resolved or unresolved, allows this to be achieved.)

TABLE II: PREPROCESSED DATA

Dispute ID	Dispute Type (encoded)	Participant 1 Age (normalized)	Participant 2 Age (normalized)	Communication Length (normalized)	Resolution Status (encoded)
1001	0 (Contract)	0.78	0.67	0.83	1 (Resolved)
1002	1 (Consumer)	0.51	0.70	0.50	0 (Unresolved)
1003	2 (Employment)	0.96	0.75	0.67	1 (Resolved)
1004	3 (Property)	0.63	0.55	1.00	0 (Unresolved)

Apart from the resolution state, the training data holds the traits drawn from the conflicts. Among other things, these elements are participant demographics, phrase frequency, and sentiment scores. Training uses a loss function derived from the classification accuracy. Techniques for hyperparameter tuning include grid search and cross-validation, which help to maximize this loss function.

Over the course of automated mediation, the model is trained to connect different aspects of the conflict with effective resolution tactics. These methods are then used to offer possible solutions. Using measures connected to accuracy, precision, and recall, the model's performance is assessed.

An illustration of the training data at this level is shown in Table IV.

TABLE IV: TRAINING DATA

Dispute ID	Sentiment Score	Keyword Frequency (Refund)	Keyword Frequency (Breach)	Tone (Formal)	Resolution Status (encoded)
1001	0.20	2	0	Yes	1 (Resolved)
1002	-0.50	1	1	No	0 (Unresolved)
1003	0.30	0	0	Yes	1 (Resolved)
1004	-0.10	3	2	No	0 (Unresolved)

E. Automated Mediation

The model trained is then used for automated mediation. The system examines the communication data connected to the new conflict, extracted traits including sentiment, keyword frequency, and tone, and then applies the computer learning model created to predict the most likely path of conflict resolution.

The system suggests a mediation strategy depending on the results of the model. The following are examples:

- Automatic Suggestion of Solutions: The system could automatically offer a solution should the conflict's resolution be expected to be straightforward (for example, if it concerns a refund).
- Human Mediation Involvement: If the model show that the issue is complex, for instance, a breach of legal contract, the system can advise involving a human mediator to ensure that every side is treated equitably and that the matter is addressed totally.

If the conflict be somewhat straightforward, the system might handle mediation by itself. Dealing with more complicated issues could imply the system can only assist by recommending a list of possible solutions based on the facts it has examined. The last result would be decided by a human mediator. An illustration of one of the mediation recommendations the algorithm has generated is Table V.

TABLE V: AUTOMATED MEDIATION SUGGESTIONS

Dispute ID	Predicted Resolution Strategy	Suggested Solution	Involvement of Human Mediator
1001	Refund	Refund $200 to Participant 1	No
1002	Contract Breach	Legal Consultation	Yes
1003	Consumer Complaint	Replace Damaged Product	No
1004	Property Dispute	Negotiation for Compensation	Yes

F. Post-Mediation Analysis

A post-mediation research assesses the efficacy of the mediation procedure after its conclusion. The major objective in this case is to evaluate the extent of the solution (for example, to determine whether both sides are satisfied with the outcome) and to collect feedback so that changes may be made moving forward.

The system's feedback from participants in the mediation process can be applied to the following ends:

- Refine the Model: The feedbacks enable the model to recognize which tactics were more successful in particular types of disputes and to fine-tune its forecasts for the future.
- Evaluate Performance Metrics: The degree of user enjoyment, the time needed to solve issues, and the correctness of solutions all assist to gauge the success of the mediation system.

The table VI below illustrates the feedback data gathered during the post-mediation study.

TABLE VI: POST-MEDIATION FEEDBACK DATA

Dispute ID	Participant Satisfaction (1-10)	Resolution Time (minutes)	Outcome Accuracy (1-5)	Model Improvement Feedback
1001	8	15	4	Yes
1002	5	30	3	No
1003	9	10	5	Yes
1004	6	45	2	No

Using the feedback data, the system may evaluate not only the degree of participant pleasure but also the correctness of the results. The outcomes are returned to the model so that it can always improve its ability to predict the future and provide mediation strategies.

The research calculate a resolution time using the following formula:

$$T = \frac{\sum_{i=1}^{N} t_i}{N} \qquad 2$$

Where:

T is the average resolution time across all disputes.

ti is the resolution time for the i-th dispute.

N is the total number of disputes considered.

Among the most crucial performance criteria is the average time it takes to resolve conflicts utilizing the proposed automated mediation system. This helps to determine the average time needed.

IV. Results And Discussion

Simulations of online dispute resolution scenarios across a spectrum of different kinds of conflicts are run within the experimental framework (Table VII). Originally designed to mimic many dispute scenarios and use various resolution strategies, SimuResolve is this software tool. To speed the training of machine learning models, the experiment is run on a cloud-based computing system employing Amazon Elastic Compute Cloud instances and GPU support. This method is evaluated in comparison to three other presently employed techniques: Traditional ODR Systems, AI-Powered ODR Systems and Hybrid ODR Systems.

TABLE VII: EXPERIMENTAL SETUP

Parameter	Value
Simulation Tool	SimuResolve
Computing Platform	AWS EC2 Instances
Model Training Technique	Supervised Learning
AI Algorithm	Random Forest
Mediation Mode	Hybrid (AI + Human)
Dispute Types Simulated	5 (Contract, Consumer, Employment, Property, Family)
Simulation Runs	1000

V. PERFORMANCE METRICS

1. Resolution Time: This policy specifies the typical time required to settle a dispute. A lower score indicates a more efficient method.
2. User Satisfaction: User satisfaction is a gauge of the perceived fairness and efficacy of the solution. Rating the solution from one to 10 defines it.
3. Accuracy of Resolution: Accuracy is the percentage of conflicts that are successfully resolved, hence determining a resolution that is mutually acceptable.
4. Cost Efficiency: Resolving a disagreement has a specific resource cost; lower numbers suggest a more efficient use of resources. Cost efficiency is defined by resource use.

TABLE VIII: RESOLUTION TIME COMPARISON (IN MINUTES)

Method	250 Runs	500 Runs	750 Runs	1000 Runs
Traditional ODR Systems	45	42	40	38
AI-Powered ODR Systems	38	35	32	30
Hybrid ODR Systems	30	28	25	22
Proposed ODR System	20	18	16	15

In table VIII, when compared to the techniques already in use, the proposed approach significantly reduces the time required for resolution. But by the time the thousandth run is complete, the recommended approach indicates a fifty percent gain in efficiency over traditional ODR systems. Most ODR systems require the most time.

TABLE IX: USER SATISFACTION COMPARISON (1-10 SCALE)

Method	250 Runs	500 Runs	750 Runs	1000 Runs
Traditional ODR Systems	5	5.2	5.4	5.5
AI-Powered ODR Systems	6	6.3	6.5	6.8
Hybrid ODR Systems	7	7.2	7.5	7.8
Proposed ODR System	8	8.2	8.5	8.8

The table IX, often, the ODR system developed in terms of user satisfaction beats current substitutes. Over a thousand runs, it earns an average score of 8.8, which is far higher than the ratings achieved by AI-powered systems (6.8) and traditional systems (5.5), suggesting that it provides a better user experience and inspires more trust in the process.

TABLE X: ACCURACY OF RESOLUTION COMPARISON (%)

Method	250 Runs	500 Runs	750 Runs	1000 Runs
Traditional ODR Systems	70	72	73	74
AI-Powered ODR Systems	75	77	79	80
Hybrid ODR Systems	80	82	84	85
Proposed ODR System	90	91	92	93

In table X, when compared to conventional systems, which attain an accuracy of 74%, and AI-powered systems, which achieve an accuracy of 80%, the proposed system clearly outperforms in terms of resolution accuracy, obtaining 93% accuracy at 1000 runs. This indicates that the proposed approach can more systematically and efficiently resolve disputes.

TABLE XI: COST EFFICIENCY COMPARISON (IN USD)

Method	250 Runs	500 Runs	750 Runs	1000 Runs
Traditional ODR Systems	500	480	470	460
AI-Powered ODR Systems	450	430	420	400
Hybrid ODR Systems	350	340	320	310
Proposed ODR System	200	180	170	150

The table XI, when compared to more conventional approaches, the ODR system that has been created demonstrates notable cost reductions. By the time the thousandth cycle is complete, the cost has fallen to $150, which is more than sixty-five percent less than conventional methods. This underlines the cost benefits of using the proposed method.

The cross-performance indicator comparison reveals that the proposed ODR system's implementation has generated significant advantages. When compared to conventional approaches, the proposed approach was able to reduce the average time required for resolution by fifty percent, hence enhancing the level of efficiency.

VI. CONCLUSION

The proposed ODR system demonstrated notable advantages over traditional systems, artificial intelligence-driven systems, and hybrid systems. With a 25% rise, the proposed method surpasses the systems already in use in terms of precision of resolution by offering more dependable and efficient resolutions. Moreover, the system is rather affordable since it reduces costs by more than 65%, which qualifies it as an economically viable choice for more general use.

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