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REVOLUTIONIZING SENTIMENT ANALYSIS IN LITERARY TEXT 'THE IMMORTALS OF MELUHA' THROUGH A HYBRID CNN-RNN ARCHITECTURE AND ADVANCED FEATURE TECHNIQUES

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ABSTRACT

Sentiment analysis has emerged as a pivotal task in natural language processing, enabling the automated interpretation of emotions and opinions expressed in text. The study presents a novel method for summarizing and sentiment analysis of the literary work "The Immortals of Meluha." A hybrid CNN-RNN architecture is used in the suggested methodology, along with sophisticated feature extraction and selection procedures that makes use of the Artificial Gorilla Troops Optimizer (AGTO) model. The first stage extracts the textual information, followed by preprocessing techniques including tokenization, stemming, and the removal of special characters, stop words, and nulls. Two methods are used in feature extraction: the Term Frequency-Inverse Document Frequency (TF-IDF) methodology, which measures word significance in the dataset, and the Assimilated N-Gram (ANG) method, which gathers contextual data. The most distinctive characteristics are found using the AGTO model, which optimally choose characteristics and improve the effectiveness of classification. The development and execution of a hybridized CNN-RNN architecture, which combines Long-Short Term Memory (LSTM) and Convolutional Neural Networks (CNN), is the basis of the present paper. This design helps with sentiment evaluation and summarizing positions by capturing local as well as international relationships in the textual material efficiently. The results of the experimental assessment show that the CNN-RNN methodology outperforms other approaches, including word2vec+CNN, doc2vec+LR, and one-hot+LR with higher accuracy of 98%. The suggested method's effectiveness is further confirmed by measures such as area under the curve (AUC), precision, recall, and F-measure. The study is unusual because it takes an integrated strategy, combining a hybridized deep learning architecture with sophisticated preprocessing, feature extraction, and selection algorithms. The important contribution of the suggested technique to natural language processing—particularly in the areas of sentiment analysis and summarization—is highlighted in the study's conclusion.

Keywords: *Artificial Gorilla Troops Optimizer, Deep Neural Networks, Meluha, N-Gram Approach, Sentiment Analysis*

1. INTRODUCTION

The term "myth," which is derived from the Greek word "mythos," denotes a tale or word. Myths are ethically dubious stories that are thought to be real, are typically set in the distant past, and feature legendary or otherworldly beings. They're moral tales emphasizing a more positive outlook on life or a commendable deed in society. The Puranas fall under the category of Hindu History. Substantial lifestyle, spending, and recreation shifts have occurred in India since liberalization, and these changes have been even more pronounced after the turn of the century [1]. In relation to the area of inspiring leadership, Shiva offers one of the best models for the same thing. Tripathi provides a more thoughtful and appropriate response than anybody else in his very first book, "Shiva! The Mahadev is a highly revered charismatic leader, the God of Gods, slayer of evil, loving lover, ferocious warrior, and brilliant dancer [2].

In this section, CNN is explained, the convolution stage employs a number of filters to analyze the various characteristics of the input layer. After the conversion procedure, output layer displays results of the analysis using Rectified Linear Unit (ReLU) function of activation. There are about two convolutional layers involved in the pooling process [3]. The term "end- system development for a variety of purposes is aided by deep learning. The aforementioned systems outperform conventional methods and are capable of extracting information without bias. The two best methods for categorizing music data are CNN and RNN [4], whereby spatial relationships in features domains are better captured by CNN [5], and RNN effectively manages the temporal constraints of sequential data. Many literary works categorized the GTZAN dataset, that became the standard for musical assessment [6].

Deep learning's introduction to Natural Language Processing (NLP) studies has sparked incredible fascination with fields like Sentiment Analysis, Theme Modelling, Part of Speech (POS) tagging, Text Summarization, etc. People no longer hesitate to publicly voice their ideas on the internet thanks to Web 2.0's growth [7]. By enabling the learning of a set of variables that may be employed across several layers at various depths, CNNs are able to include one component of such flexibility. Our method successfully enables learning the length (iteration count) as well as the material of several loops defining the resultant CNN since the structure of reuse is itself learnt [8]. For the objective of identifying shill attempts in various applications and scenarios, a variety of architectural architectures that combine advantages of RNN and CNN have been proposed. The most common RNN and CNN combinations for shilling attack detection in the literature are CNN-LSTM, cascade CNN-RNN, CNN-GRU, and CNN-LSTM-AM. Although it is helpful for the identification of shilling assaults point, CNN neglected to add the items rating time distribution cases anywhere anomalous patterns exposed by rankings order [9].

In literature, target-dependent sentiment categorization is frequently viewed as a specific type of text classification issue. The majority of current research use supervised machine learning techniques to create sentiment classifiers, such as supported vector machines or neural network methods that are feature-based [10]. Long-term short-term memory (LSTM) and gated recurrent unit (GRU) suggested solutions to these issues [11]. Considering the factors that follow and prior background while using bi-directional LSTM (Bi-LSTM) with bi-directional GRU (Bi-GRU) [12] [13]. These methods might more effectively address the challenges of sequence modelling by linking both forward and backward hidden layers. But the high-dimensional space for input in spreadsheet applications maximizes model complexity and makes optimization difficult. Thus, sentiment analysis still has its limits [14]. In fact, SA forbids the inspection of particular details, acceptable levels of information, portions, elements, or functionalities of the entity that end users have remarked on and evaluated. Seldom do previous research studies use sentiment analysis to detect emotions. Consequently, a useful method for concentrating on feelings-based emotions is required. To do more in-depth research that can highlight certain features of goods or services that customers prefer or hate, new methods and techniques are required. In this situation, element-based emotional evaluation is used to assess the user's opinions for each distinct feature of the service or product.

Aspect-based emotional assessment is now gaining popularity in the scientific community as a result of the growth of novel and inventive methods and procedures with sentiment analysis foundations [15]. Identifying entity features from the text, extracting the words and phrases used to represent the aspects, figuring out the sentiment or opinion polarity for every aspect, and finally identifying the feelings are the main tasks aspect-based emotional sentiment analysis. Sadly, majority of methods and procedures now in use reflect various interpretations of what "sentiment" is and how it is quantified. This issue, which causes a great deal of misunderstanding between concepts that are extremely different from one another (such as emotion, sentiment, emotional reaction, and opinion), is seen to be a significant shortcoming of contemporary computer approaches used in everyday life. Because the Internet of Things is so prevalent and imaginatively diverse, new devices are continuously being integrated into it, either as actual IoT endpoints or as IoT branching [16].

In this study, we propose a revolutionary approach to sentiment analysis in the literary text "The Immortals of Meluha". Recognizing the need for advanced techniques to unravel the complexities of the narrative, we introduce a Hybrid CNN-RNN architecture coupled with sophisticated feature extraction methods. Leveraging the power of AGTO for optimal feature selection, our methodology involves meticulous preprocessing steps such as stemming, tokenization, and removal of stop words, ensuring the text is standardized and noise-free. We employ two feature extraction approaches, the ANG model capturing contextual information and the TF-IDF model measuring word importance. The proposed architecture combines the strengths of CNN and RNN to effectively capture both local and global dependencies in the textual data.

The key contribution of proposed work is listed below.

- The research introduces a novel approach to sentiment analysis by employing a Hybrid CNN-RNN architecture. This architecture combines the strengths of CNNs and RNNs to effectively capture both local contextual information and sequential dependencies in textual data.
- The study employs a sophisticated feature extraction process that amalgamates the ANG and TF-IDF. ANG extracts N-grams while considering semantic relationships, enabling a richer representation of textual features. TF-IDF captures word importance, enhancing feature discriminative power.
- The research introduces the AGTO for feature selection. This novel approach mimics the foraging behavior of gorilla troops to dynamically select a subset of features that contribute most effectively to sentiment classification, improving efficiency and performance.
- The proposed Hybrid CNN-RNN architecture achieves state-of-the-art accuracy in sentiment analysis. It showcases robust performance across different sentiment classes, indicating its effectiveness in understanding and classifying nuanced sentiments within the text.
- The combined strategies of advanced feature extraction, innovative feature selection, and the hybrid architecture significantly enhance sentiment analysis precision. This contributes to more accurate automated interpretation of emotions and opinions expressed in the text.
- Apart from technical advancements, the research also provides insights into the sentiment dynamics of "The Immortals of Meluha," offering a deeper understanding of how sentiments are expressed and evolve within the context of the literary work.
- The study opens avenues for future research by suggesting the extension of this approach to other literary works and genres. Additionally, it highlights the potential adaptation of the methodology to analyze sentiments in different languages, broadening the applicability of the proposed approach.

The rest of this paper is structured as follows: Section 2 covers extensive past research on the sentiment analysis. Section 3 discussed about problem statement, Section 4 proposed pre-processing, feature extraction, and Hybridized CNN-RNN. Section 5 experimental evaluations, this part contains mathematically formulated system models for accuracy, precision, specificity, f1-score, recall and sensitivity. Section 6 concludes the paper.

2. RELATED WORKS

Qiannan Xu et al. [17] proposed a multi-attention network (MAN) for aspect-based semantic classification. MAN used an inter- and intra-level attention mechanism. Previously, MAN used a transformer encoder rather than a sequential process to minimize training time. The input sentence was encoded in parallel by a transformer encoder while preserving long-distance sentiment relations. Recently, MAN applied the local attention and global attention module to collect inverse-grained context-aspect interactive data. However, experimental results showed that MAN performed better in aspect-based sentiment analysis; An additional deep network would be needed to increase performance.

ZhanchengRen et al. [18] had developed multi-label personality detection approach based on neural network in which the emotional and semantic features were combined. For semantic extraction of text, sentence level embedding was generated with Bidirectional Encoder Representation from Transformers (BERT). In order to estimate sentiment information, text sentiment analysis is invoked with sentiment dictionary.

ShiqiangGuo et al. [19] had proposed personalized job resume matching system ResuMatcher for job searching portal. More accurate and relevant search results were obtained using keyword search with respect to the content of resume. Statistical similarity measure was used for ranking and estimating the similarity between job postings and resume. The computational complexity and time consumption is reduced with this approach.

Vrinda Mittal et al. [20] had developed Natural Language Processing (NLP) to handle the issue of finding best match for the given job. Detailed information from the candidate resume is extracted without considering the resume format such as colour, size and font. Relevant information needed for the recruitment process can be extracted with

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named entity recognition of Stanford CoreNLP system. By using this approach, the resume prediction capability is improved and more convenient and accurate prediction is further required.

Pradeep Kumar Roy et al. [21] had investigated automatic machine learning based approach for recommending right candidates resume to HR based on the description of job. Initially, the resume was classified into various types then it is selected for recommendation based on the similarity index of job description. The estimation accuracy is improved with linear SVM classifier.

Qihuang Zhong et al. [22] presented knowledge graph augmented network (KGAN) that intends to efficiently integrate external information explicitly contextual syntactic knowledge. Specifically, KGAN uses a multi-viewpoint representation of semantic features, meaning syntax-, context-, and knowledge-based. Initially, KGAN learned syntactic and context representation in addition to obtaining semantic characteristics. Then, the information graph integrated in embedding space using KGAN, depending on how aspect-based knowledge representation further achieved through the attention mechanism. Finally, a hierarchical fusion module used to balance these multi view representations at the local and global scales. Limitations of this model include less accuracy, F1, etc.

Srividya et al. [23] proposed that the sentiment of the whole text is that the former is identified by difference between sentiment analyses and aspect-based, while latter, who examines and categorizes whole text, finds the corresponding sentiment for each of them. Correct sentiment prediction also plays an important role in sentiment context. Aspect-based contextual sentiment analysis is an amalgam of neuronal focus mechanisms and LSTM called NA-DLSTM according to a new model. In terms of accuracy, the F1 scores are promising compared to other NA-DLSTM (Neural Attention based Deep Long Short-Term Memory) models.

He et al. [24] proposed adequate focus on significant profound connections between the global environment and element emotion polarities. Additionally, investigations on Chinese ABSA tasks and international ABSA tasks are few. We suggest an international approach to learning called LGCF that depends on the interaction acquisition of global as well as local contextual focus and is based on the regional context focus process. It is capable of learning the connection among local circumstances and target aspects as well as the relationship between global context and goal aspects concurrently, as compared to the previous models. The algorithm is also capable of analysing feedback in both Chinese and English successfully. Additionally, the outcomes in the elimination trial confirm the efficacy of every component in the LGCF.

The conceptualization of this work stems from the persistent challenge of accurately deciphering sentiment in literary texts. Existing sentiment analysis methods often fall short in capturing the nuanced emotions and intricate narrative structures present in literary works, hindering a deeper understanding of the author's intended meaning and the reader's subjective experience. This limitation is particularly relevant in the context of modern literature, where authors employ increasingly complex narrative techniques and delve into multifaceted themes. Theoretical underpinnings of sentiment analysis need refinement to accommodate the intricacies of literary language, making it a real and pressing problem. A meaningful outcome from this study holds the potential to enhance the field of natural language processing, offering scholars, researchers, and literary enthusiasts a more nuanced and accurate tool for sentiment interpretation in literary texts, thereby enriching the comprehension and appreciation of complex narratives.

3. PROBLEM STATEMENT

The work aims to enhance the sentiment classification process by accurately determining the sentiment expressed in the text, whether it is positive, negative, or neutral. Additionally, it aims to improve the summarization process by generating concise summaries that capture the main points and key aspects of the book. The primary motivation behind this problem statement is to leverage the advancements in deep learning techniques, particularly the combination of CNN and RNN, to overcome the challenges associated with sentiment classification and summarization tasks for a specific literary work. By developing a hybridized CNN-RNN architecture, the authors aim to provide an effective solution that can automate and enhance these tasks, enabling a deeper understanding and analysis of the book's content [25].

4. PROPOSED METHODOLOGY OF MYSTERIES OF MELUHA

Obtain the textual data from the book "The Immortals of Meluha" by Amish Tripathi, which will serve as the dataset for sentiment classification and summarization tasks. Cleanse and prepare the text

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data for further analysis. This involves several steps such as stemming, segmentation, tokenization, case folding (converting all text to lowercase), and removal of stop words, nulls, and special characters. These preprocessing techniques help in standardizing the text and reducing noise. Apply feature extraction techniques to represent the textual data in a suitable format for classification. In this research, two approaches are used: the ANG and TF-IDF. ANG captures the contextual information by considering multiple word combinations, while TF-IDF measures the importance of words in a document relative to the entire dataset. To enhance the classification performance, select the most informative and relevant features from the extracted feature set. The Artificial Gorilla Troops Optimizer (AGTO) model is utilized for optimal feature selection, which employs a nature-inspired optimization algorithm to identify the most discriminative features. Design and implement a hybridized CNN-RNN architecture for sentiment classification and summarization tasks. This architecture combines the strengths of CNN and RNN to effectively capture both local and global dependencies in the textual data. Figure 1 shows the flow diagram of unveiling the mysteries of Meluha through a hybridized CNN-RNN.

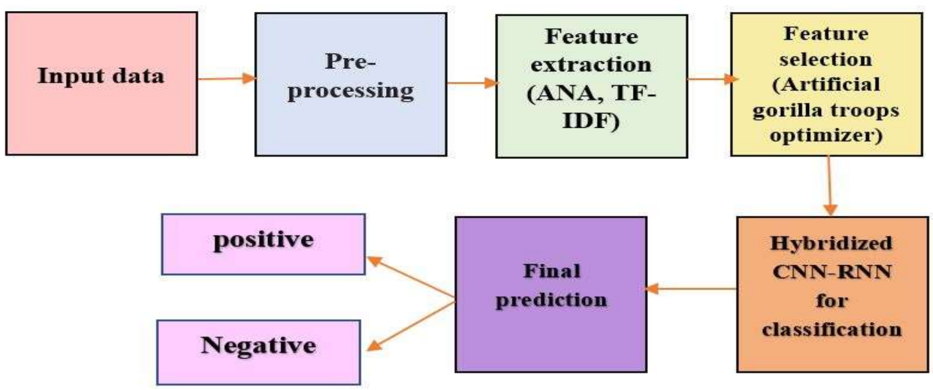

Figure 1: Flow Diagram of Unveiling the Mysteries of Meluha Through a Hybridized CNN-RNN

4.1. Data Collection

The purpose of this study's paper is to ascertain how Shiva the man is distinct from Lord Shiva and the degree to which the author is successful in portraying the Shiva Trilogy as a spiritual manual for the current age. Amish decides to base his story on the most complex god from Hindu mythology. Amish modifies the Shiva Purana by portraying Lord Shiva as a mortal man who eventually rises to heavenly grandeur as a result of his karma. The story has a human-centered approach that enables the author to use Shiva Trilogy as a spiritual guide for future generations by enabling them to find Mahadev within of them to take in evil and perspire righteousness. Strangely, the events in Tripathi's Shiva narrative begin approximately 1900 BCE. The Indus Valley Civilization then starts to disappear. He creates a work of Vedic fiction that describes the Indus Civilization's topography, Vedic gods, religion, and caste structure. When Shiva visits Lord Mohan's Temple, Brahaspati and Brahma become scientists, and surgeons undertake aesthetic procedures, Mohenjo Daro changes into Mohan Jo Daro. According to Tripathi, a fabled country where the splendour of Harappan civilisation meets Vedic religion, American vernacular, and even contemporary conveniences like restaurants, exists. The near-perfect empire of Meluha was founded many years ago by Lord Ram, one of history's greatest kings. The renowned Saraswati, the kingdom's main river, is gradually drying up and destroying the once-proud empire and its Suryavanshi kings. The Chandravanshis, an enchanted race with physical defects, have allied with the Nagas in the east, where they suffer catastrophic radical assaults.

4.2. Pre-processing

The preprocessed data are used to enter the model and get the best results. Stemming, segmentation, tokenization, case folding, stop word removal, null value, and special characters were removed during preprocessing. A data mining method called processing comprises transforming the raw data into an approachable format.

Preprocessing the dataset to a textual form before putting it into machine learning algorithms is a vital step. So many phases of the procedure were recorded. The "reviews" column and the empty rows were discarded first. The natural language toolkit library (NLTK), a machine learning package for natural language processing (NLP), is also used.

Although the analysis produces positive findings, it is necessary to occasionally rectify spelling errors order to ensure that sense of text is not lost. The most suitable correction is employed by the spellchecker to identify misspelt words and recommend a repair. Tokenization is the approach that is most frequently employed when working with text data. The process is to turn sensitive data into tokens. The text data is tokenized and filtered using sentiment analysis to eliminate any extraneous tokens. Stop words are words that are regarded as unhelpful in sentiment analysis. In other words, eliminating such terms won't have any impact on the model's output or the analysis's precision or recall. They don't help us comprehend the sentence's or review's genuine meaning. Due to their size, preserving them would demand more computational resources for really big datasets. Stop words are eliminated using two techniques. The first technique, which used the NLTK library, found tokens that included stop words and removed them from the reviews, such as (e.g., a, it, is, that, and but). When a word has a frequency more than 50% but was eliminated due to poor usage, the second technique is used. It is applied to words that need to be deleted from the NLTK stop words collection and have a frequency larger than 50%. Unlocked, time, mobile, and phone are a few examples. Throw out any uncommon terms that only appear a few times as well. To remove punctuation marks, use an exclamation point, a full stop, and a comma. Lemmatization, also known as stemming, removes both prefixes and suffixes to bring words back to their original form. It was finished with the aid of the NLTK library. Words with comparable meanings are connected via lemmatization. Case-folding is changing lowercase characters in a string of characters to their uppercase equivalents. When referring to XML, the word "case-folding" merely denotes uppercasing [18]. Figure 2 shows Preprocessing steps.

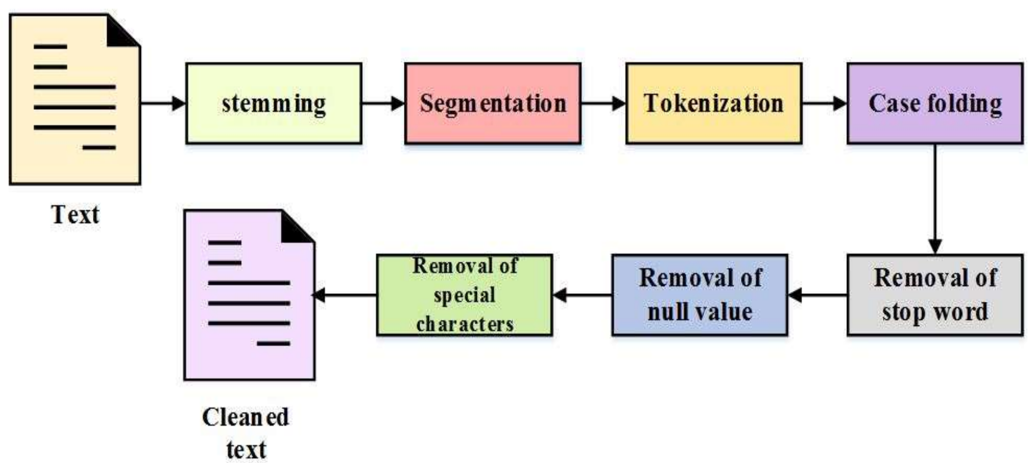

Figure 2: Preprocessing Steps

4.3. Feature Extraction

4.3.1. Assimilated N-Gram Approach (ANG)

Construct a hybrid static ANG of the vector. Each phrase transforms a vector that runs a predetermined window of size N and uses N-grams to create into overlapping ANG. N-grams decompose texts and phrases into words as a statistical language model (LM) $c_i(c_1, c_2, \ldots, c_n)$. N-gram presupposes a Markov system and specifies context in the most popular LM $\phi(C_{i-1})$ as;

$$\phi(C_{i-1}) = c_{i-n+1}, c_{i-n+2}, \ldots, c_{i-1} = t \qquad (1)$$

Since there is no context, it is just a random assortment of words if N-1. The N=2 context becomes $\phi(C_{i-1}) = c_{i-1}$, c_i considered 2 words. The N=3 context becomes $\phi(C_{i-1}) = c_{i-2}, c_{i-1}, c_i$ considered 3 words.

Technically speaking, an ANG is therefore a textual sequence of N successive "textual units"

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taken from a certain phrase or text. According to the setting of fascination, a "textual unit" may be acknowledged as an element when a vector illustration of the N-grams of is transformed into a word or a phase. The N-gram is recognized at the word level in this investigation.

Each N-gram in a vector that resembles the text being studied corresponds to a vector coordinate. The value of this coordinate may represent frequency, occurrence, or another measure, depending on the text. The unigram is the simplest n-gram that may represent the standard "bag-of-words" (BOW) format, when n = 1. Because they are straightforward and efficient, ANG models are frequently employed on NLP tasks. They challenge the vector from a sizable text dataset by creating the vector. Each phrase is transformed into a bag of n-grams and represented as an occurrence frequency vector, with information contained in n-grams of original text being disregarded. As a result, the vector has a large number of pointless and redundant characteristics. In this research, we suggest a novel N-gram model-based approach to extraction from feeling at the sentence level analysis. One of three-word N-grams (N = 3) that describe a phrase is used to identify a sentiment term. As a consequence, after creating the three word N-grams, we invoke a sentiment dictionary that points to an N-gram with the emotion phrase in it [26].

Three words make up the N-gram that was discovered. A hybrid vector is created for statement using three words, their Part of Speech (POS) tags, their emotion orientations. Context is as follows when N = 3; $\phi(C_{i-1}) = c_{i-2}, c_{i-1}, c_i$ for words; $\phi(L_{i-1}) = L_{i-2}, L_{i-1}, L_i$ for POS tags and; $\phi(K_{i-1}) = K_{i-2}, K_{i-1}, K_i$ for semantic orientation.

Words, POS tags, and semantic orientations can be combined as shown below to provide sentiment aspects (A):

$$\phi(Y_{i-1}) = C_{i-2}, C_{i-1}, C_i, L_{i-2}, L_{i-1}, L_i, K_{i-2}, K_{i-1}, K_i \quad (2)$$

4.3.2. Term Frequency Inverse Document Frequency (TF-IDF)

Term frequency (TF) and inverse document frequency (IDF) are combined in TF-IDF. Given that it directly uses the original phrase frequency value, the TF representation is straightforward term weighting scheme (TWS). On premise that words with higher term frequency values are more important than those with lower term frequencies, the TF model is established. It just depends on how frequently a phrase appears in a local document. Due to its lack of knowledge regarding collecting frequencies, TF is unable to differentiate between important and unimportant documents. The inverse document frequency (IDF), which was introduced with a focus on collection frequency, aims to improve a text classification term's ability for discrimination. Document frequency (DF) is a metric used to gauge how often a phrase appears in documents. When determining the importance of a phrase, it is preferred if it appears in fewer papers as opposed to more records. Follow these procedures to find the IDF value of a certain term:

$$IDF(h, x, X) = \log \frac{|X|}{DF(h, X)} \quad (3)$$

$DF(h, X)$ represent the DF value of terms h in corpus X. Therefore, sign denotes the total number of documents in corpus X. To prevent infinity in some extreme instances, the formula is occasionally optimized, as seen below:

$$IDF(h, x, X) = \log \frac{|X|+1}{DF(h, X)+1} \quad (4)$$

The TF value was then included in the computation, expanding the IDF approach. The most used word weighting strategy is the TF-IDF combo. An international statistics metric that resembles IDF is TF-IDF. Below is a diagram of the TF-IDF classical structure:

$$TF - IDF(h, x, X) = TF(h, x) * IDF(h, x, X) \quad (5)$$

It represents the weight of term h of document x in corpus X, and $TF(h, x)$ represent the BTF value of term h in document x. As a result of its original design, TF-IDF does not perform well in the domain of text classification. TF-IDF-based term weighting methods have been optimized from various perspectives in a number of research studies [27].

4.4. Feature Selection

Features were chosen to create a predictive model with fewer input variables. In some circumstances, a model's performance and computing cost can be improved by lowering the number of input variables. FS can address the issues of having both too much and insufficient valuable data. Features should be chosen by determining the bare minimum of relevant columns in the data source before creating a model. an FS technique for

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improving machine learning accuracy. Because the most important variables were chosen, and the redundant and unimportant ones were removed, the algorithms are therefore more likely to produce correct predictions.

A FS problem with low n_a and high classification accuracy considered the best. Equation uses the fitness function to test the strategies and find a balance between the accuracy of classification and the number of attributes (n_a).

$$Fitness = \alpha\gamma_r(X) + \beta\frac{|J|}{|M|} \qquad (6)$$

Here, $\alpha \in [0,1]$, $\beta = (1-\alpha)$, $\gamma_r(X)$ indicates the rate of a classification error, $|J|$ indicates the cardinality of the n_a, $|M|$ indicates the database attributes. The α and β denotes two variables concerning superiority and subset length, respectively.

4.4.1 Artificial Gorilla Troops Optimizer (AGTO)

Populations in FS can only choose one of two alternatives because it is a binary optimization procedure. A one-dimensional vector is used to represent any solution; its length is determined by the number of attributes (n_a) in the database. A cell's value can be either 0 or 1, with 1 designating that the feature has been selected and 0 designating that it has not. FS issues are multi-objective optimization issues with competing goals, such preserving classification accuracy while selecting the shortest n_a.

Because they are motivated by the collective intelligence of natural animals, Meta heuristics are crucial in resolving optimization problems. A brand-new Meta heuristic algorithm called the GTO was motivated the social intelligence of gorilla troops in the wild. This study, the social behavior of gorillas is mathematically characterized, and new approaches to exploration and exploitation are developed. A group of adult male gorillas, known as silverbacks, and multiple adult female gorillas with their young make form a troop of gorillas.

$$ICX(t+1) = \begin{cases} (UB-LB)\times ra_1 + LB, & rand < p, \\ (ra_2 - C)\times X_{ra}(t) + L\times H, & rand \geq 0.5, \\ X(i) - L\times(L\times(X(t) - ICX_{ra}(t)) + ra_3\times(X(t) - (ICX_{ra}(t))), & rand < 0.5. \end{cases} \qquad (7)$$

$ICX(t+1)$ Denote ANA position in the next t iteration. $X(t)$ is a TF-IDF position. ra_1, ra_2, ra_3 In addition, $rand$ are each cycle updates a set of random numbers in the range of 0 to 1. p is a component with a range of 0 to 1 and a required value prior to optimization process. It represents the top and bottom limits of the variable, correspondingly X_{ra} Is one distance of randomly selected from the entire data and ICX_{ra}. Finally, C, L and H are derived using calculations below,

$$C = V \times (1 - \frac{It}{MaxIt}) \qquad (8)$$

Where, $MaxIt$ is total value of iteration perform optimization operation,

$$V = \cos(2\times r_4) + 1 \qquad (9)$$

Here, $\cos$ shows that functions and r_4 is Random numbers between 0 and 1 that change between iterations.

$$L = C \times l \qquad (10)$$

Where, l represents a random number between -1 and 1.

$$ICX(t+1) = L \times M \times (X(t) - X_{best_{distance}}) + X(t) \qquad (11)$$

$X(t)$ is the position's present direction with respect to $X_{best_{distance}}$.

$$M = \left(\left|\frac{1}{N}\sum_{i=1}^{N} ICX_i(t)\right|^s\right)^{\frac{1}{s}}, \qquad (12)$$

Where, $ICX_i(t)$ denotes each place in the iteration t. N Represent total amount data. s is also approximated using below equation,

$$s = 2^L \qquad (13)$$

The resulting solution may be infeasible un terms limitations, but they can be made feasible by rearranging them again the fitness of offspring solutions $\min(ICX(t))$ is assigned Eqn. (14). In order to minimizing the sum of data adaptive genetic algorithm is used. Suppose the crossover probability and mutation,

$$\min(CX(t)) = \begin{cases} H + \dfrac{H_{\max} - H_{\min}}{1 + \exp((G - G_{avg})/(G_{\max} - G_{avg}))}, & G \geq G_{avg} \\ H_{\max} & G < G_{avg} \end{cases} \quad (14)$$

To calculate fitness value given by, $H_{\min}$ represent minimum probability, $H_{\max}$ denotes probability of getting maximum, G fitness of parameter, G_{avg} indicates average, $G_{\max}$ is denoted maximum fitness function of feature selection.

4.5. Feature Selection

4.5.1 Hybridized CNN-RNN Architecture for Classification

CNN is network feed forward neural networks, meaning that data only makes it forward, without loops or cycles, between the source nodes, via the concealed nodes, to the resultant nodes. The main use of such (feed forward) networks is pattern recognition. In general, CNN is effective in spotting simple patterns in data that may be utilized to create more complicated patterns in deeper or higher layers. Convolutional layers and pooling layers are the main components of CNNs. The convolutional layer's job is to identify resident combinations features from preceding layer, whereas merging layer's job is combining features with comparable conceptual properties into a single feature. Common weights, localized receptive fields, plus spatial subsampling are all combined in CNNs. One-dimensional convolutional neural networks (1D CNN) can be used to handle datasets with a limited structure. When you anticipate deriving relevant features shorter (fixed-length) parts of total feature usual and when feature's position inside segment is not crucial, a 1D CNN extremely successful. Applications for NLP frequently employ 1D CNN. Similar to this, 1D CNN may be used to solve issues when the traits of objects whose state or category being predicted are represented by vectorized data. In order to characterize any patterns or correlations inside portions of the vectors defining each item in the dataset, the 1D CNN might use extract possibly additional unfair visualizations of features. The classifier (such as an LSTM or a fully connected layer) is then given these new characteristics, and it will analyse them to create a set of outputs that will help determine the classification outcome in the end. CNNs may therefore be used as layers for feature extraction for a particular classifier, eliminating requirement for independent ranking of features and choice outside of deep learning model.

An example of a RNN is the LSTM, which, in contrast to feedforward networks, makes use of feedback and has the capacity to "memorize" portions of the input in order to employ them in prediction. Due to its ability to handle consecutive input, RNNs are frequently used in fields like recognition of speech and machine translation. RNNs employ state to investigate connection in relation to, in contrast to conventional neural networks that fully link all nodes or CNNs that explore nodes through local to worldwide layer by layer. Classical RNNs have been shown have an issue with vanishing gradients, which prevents them from having long term memory and forces them to rely on their projections only on the latest information in the sequence. Due to its ability to handle vanishing gradients, LSTM can long-term memory processing of longer sequences. A RNN called LSTM is able to comprehend contextual information from a series of characteristics. With the use of a gate function, it has capacity to add or subtract information from hidden state vector, keeping important data in the hidden layer vectors.

$$v_h = \sigma(C_{vt} t_{h-1} + C_{vd} d_h + z_v) \quad (15)$$

$$q_h = \sigma(C_{qt} t_{h-1} + C_{qd} d_h + z_q) \quad (16)$$

$$\widetilde{w}_h = \tan t(C_{\widetilde{w}t} t_{h-1} + C_{\widetilde{w}d} d_h + z_{\widetilde{w}}) \quad (17)$$

$$w_h = v_h . w_{h-1} + q_h . \widetilde{w}_h \quad (18)$$

$$k_h = \sigma(C_{kt} t_{h-1} + C_{kd} d_h + z_k \quad (19)$$

$$t_h = k_h . \tan t(w_h) \quad (20)$$

Where, v, q and k represent the outputs of three gates units, forget about the input and output ones. w means the states of the LSTM cell, d denotes the input of a cell, z and C are the cell's bias and weight matrix, t denotes the recurrent information among cell, h and $h-1$ denotes current and previous time instance, $\tanh(.)$ and $\sigma(.)$ means hyperbolic and sigmoid activation function, and the $.$ means point-wise multiplication of two vectors.

Unlike feed forward neural network, LSTM can process any length sequence and manage variable length inputs and outputs. It is capable of strong long-term memory and processing contextual data. Furthermore, LSTM can tackle the disappearing and expanding gradient difficulties that RNN may experience. It can also swiftly adjust to abrupt changes in the tread and has superior

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processing abilities in the prediction of volatile time series. The standard LSTM unit structure is built on three gate structure: input gate, forget gate, and output gate. The sequence learning framework may be used by the LSTM autoencoder structure to identify whether the workload is regular or busy. An LSTM autoencoder is made up two parts: an LATM encoder and LSTM decoder. The value stored inside the LSTM cell is not shared by the encoder and decoder, according to the fact that the encoder and decoder networks are typically separate from one another.

$$W_t = \sum_{r}^{H} \alpha_{qr} t_r \qquad (21)$$

The weight α_{qr} of each hidden state t_r is calculated by eqn. (21).

Where, $\alpha_{qr} = \dfrac{\exp(u_{qr})}{\sum_o^h \exp(u_{ik})}$ and $u_{qr} = y(G_{q-1}, t_r)$.

The decoder's input sequence begins with an initial input, and the remaining inputs constitute the decoder's output at the last time step. After receiving input, the decoding LSTM cell modifies its visible and hidden state before emitting a forecast for the present time step. Before returning the result to the decoding layers as the subsequent inputs, the layer that produces it modifies it. The LSTM encoder-decoder system can solve the workload for sequence forecasting issue when the workload at each time is simple time series data. The cluster's their workloads, nevertheless, only turn into time series data when every machine in the cluster is engaged in the same computing activity or is providing an identical application.

4.5.2 Dense Neural Networks

The DNN is a typical, multi-layered, highly linked neural network. Each of the neurons in a layer of a DNN model takes input from every neuron present in the layer below it. The concealed layers comprise the thick layers, which are the various layers. throughout the network. Multilayer perceptron (MLP) is another name for these neural networks. It consists of an input layer, output layer that makes judgements or forecasts something based on input, and there might be a lot of levels between them. A collection of input-output pairings is frequently used to train the model, which then gains the ability to simulate the correlations (or dependencies) among those inputs and outcomes. The model's fundamental component (a perceptron) results in a single Given the input weights, create an output depending on a number of real-valued inputs. Usually, a non-linear activation function is applied to the output ϑ . and it is given in eqn. (22).

$$a = \vartheta\left(\sum_{1}^{n} c_i d_i + z\right) = \vartheta\left(C^H D + z\right) \qquad (22)$$

Wherein, C stands for the weights vector, X for the inputs vector, z for the bias, and ϑ for the non-linear activated function.

4.5.3 Hybrid Models

Referring to hybrid models as ones that combine several deep learning approaches to take use of the special qualities of each methodology. As shown in Figure, the CNN-LSTM model, for instance, it will use CNN to extract neighborhood-specific n-gram characteristics, where n is based on the length of each of the filters. The CNN's max pooling layer down samples produce results to reduce the amount of dimensional which additionally aids in preventing excessive fitting. The LSTM layers are then used to identify any potential distant relationships within the attributes recorded by the CNN layers. The graphs produced by the LSTM layer are going to be passed to dense layers for extra processing before being finalized by the single unit sigmoid triggered output layer. Figure 3 displays the hybrid CNN-LSTM system.

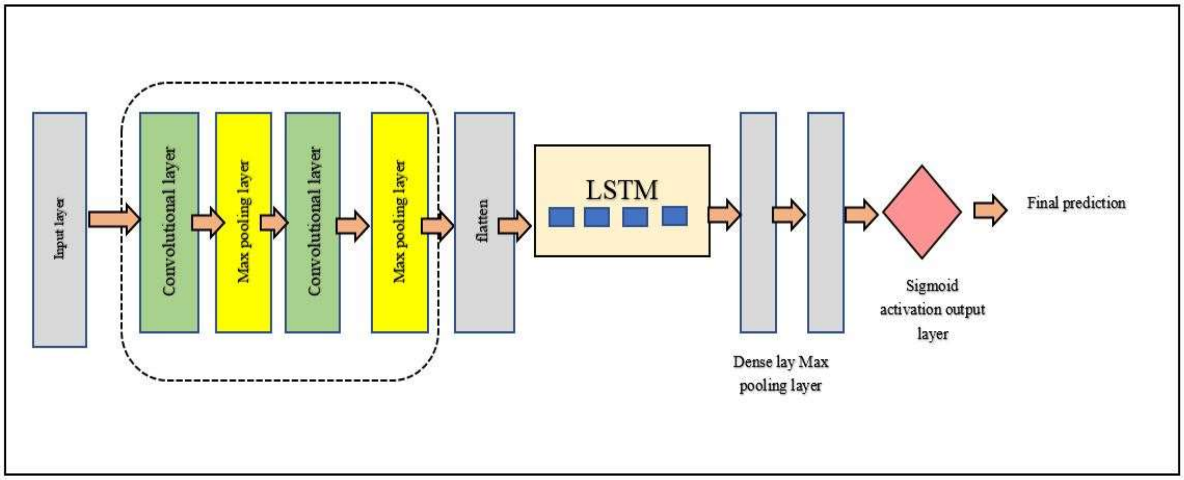

Figure 3: CNN-LSTM Hybrid Model

5. EXPERIMENTAL EVALUATION

The model performs well on the test data, which an important indicator of its efficiency is given that the model has never seen the data before. In the implementation, the word2vec+CNN, doc2vec+LR, and one-hot+ LR are existing methods. The proposed approach g will be simulated in the working platform of Python and the performance will be compared with traditional methods. The performance of proposed work will be evaluated with recital measures like accuracy, precision, f-measure, recall, along with area under the curve (AUC). The novelty of this research lies in the introduction of a Hybrid CNN-RNN architecture combined with the Assimilated N-gram approach, TF-IDF, and the Artificial Gorilla Troops Optimizer for sentiment analysis within a literary context, providing a comprehensive and accurate interpretation of sentiments in "The Immortals of Meluha".

As a result, tested the suggested the algorithm is minimized with artificial gorilla troops optimizer (AGTO) model technique using python software in a simulated environment utilizing cardiovascular dataset. The test is run on a machine equipped with an Intel(R) Core (TM) i5-3620 CPU @ 3.20GHz, 3200 Mhz, 4 core(s), 4 logical pro. And micro software 10 pro, micro soft corporation is an OS manufacturer, installed physical memory (RAM) 8GM.

The percentage of precisely expected competencies to the whole number of parts (prediction and reality) of a case determines its accuracy. Therefore, the multi-label architecture's accuracy is calculated as the mean of the precision measured across every instance.

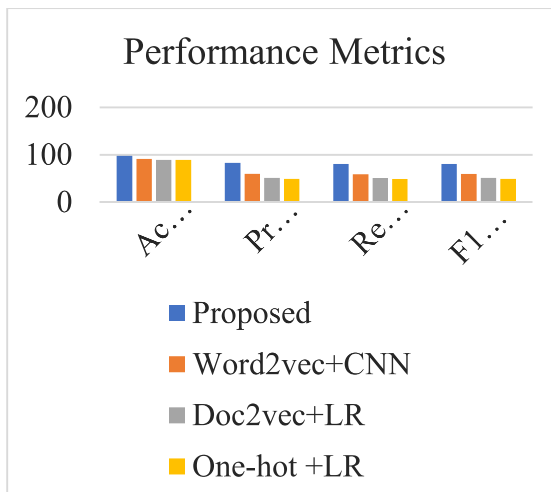

Figure 4: Performance Metrics Comparison

The Figure 4 shows results above demonstrate that the suggested technique consumes a high value and is more dependable than other current approaches. The propose methodology has an accuracy value is (98%), which is higher than other existing approaches such as word2vec+CNN, doc2vec+LR, and one-hot +LR.

The amount of each of the algorithm's precisely predicted competencies to the entire number of expected competencies for a particular situation is its accuracy. The average of the accuracy evaluated across all cases is the overall precision. The precision value in the proposed approach is high for resume corpus data set and low for existing methods. The precision value of proposed (83%), word2vec+CNN, doc2vec+LR, and one-hot +LR, were calculated using the CVD dataset. From analysis, proposed approach provides better performance than existing algorithm for resume corpus dataset. Therefore, proposed method is a very effective approach to resume skill extraction. The percentage of abilities that the model correctly predicted to all of the skills in an instance is known as recall. The mean of all the evaluated memory is the overall recall.

The graph results above demonstrate that the suggested technique consumes a high value and is more dependable than other current approaches. The proposed methodology has a recall value of 80%, which is higher than the other existing approaches such as word2vec + CNN, doc2vec + LR and one-hot +LR. The suggested hybridized CNN-RNN utilizing the Meluha dataset dataset's F-measure is shown in figure 7. proposed 80 % word2vec, doc2vec+ LR, and one-hot +LR. Based on the finding of this evaluation, it is clear that the suggested strategy outperformed previous methodologies. As a result, the proposed approach is the best scheme for resume skill extraction.

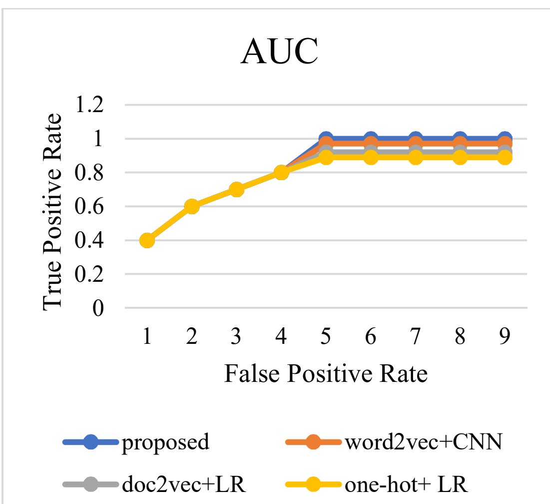

Figure 5: AUC using Meluha Dataset

AUC visualization was used to further analysis the performance of the suggested approach. The AUC curve has the TP rate as the y-axis and FP rate as the x-axis with the AUC determine to indicate models' performance. The optimal model is obtained when the AUC value is near too equal to 1. Figure 5 shows that the suggested technique outperformed other models with AUC score of up to 1.00 and 1.00 for the Meluha dataset respectively.

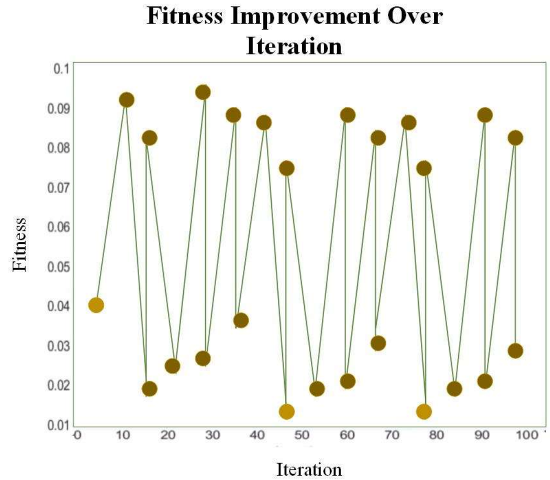

Figure 6: Fitness Improvement using Iteration

Figure 6 illustrates the "Fitness improvement using iteration" in the context of an optimization process. The plot shows how the fitness value, which represents the objective function's performance, evolves over multiple iterations of the optimization algorithm. As the iterations progress, the fitness value generally improves, indicating that the optimization algorithm is effectively converging towards a better solution. The graph provides insights into the optimization process's effectiveness and demonstrates the algorithm's ability to iteratively refine the solution towards the optimal or near-optimal point.

5. CONCLUSION

In conclusion, this work is grounded in the imperative need for a novel and robust approach to sentiment analysis in literary texts. Our argument revolves around the inadequacies of existing sentiment analysis methods in capturing the nuanced emotions and intricate narrative structures inherent in contemporary literary works. The proposed Hybrid CNN-RNN architecture, coupled with advanced feature extraction techniques such as the ANG model and TF-IDF, addresses these limitations and showcases significant improvements in accuracy. The study highlights the importance of tailored methodologies for literary sentiment analysis, recognizing the unique challenges posed by complex narratives and multifaceted themes. This work builds upon the theoretical foundation of natural language processing and sentiment analysis, extending these concepts to the realm of literature. By introducing the AGTO for optimal feature selection, we contribute a novel dimension to the feature extraction process, enhancing the interpretative power of sentiment analysis in literary contexts. The Hybrid CNN-RNN architecture, combining the strengths of Convolutional Neural Networks and Long-Short Term Memory, proves to be particularly effective in capturing both local and global dependencies within the textual data. As a stepping stone for future research, this study raises intriguing questions that merit exploration. Firstly, the generalizability of the proposed methodology across diverse literary genres and styles remains an open question. Additionally, investigating the adaptability of the Hybrid CNN-RNN architecture to other forms of creative writing, such as poetry or plays, could yield valuable insights. Exploring the impact of varying narrative structures on sentiment analysis and delving into the interpretative challenges posed by ambiguous or contradictory emotions within a text are avenues for further investigation. Moreover, the potential integration of socio-cultural factors and reader perspectives into sentiment analysis models for literature presents a compelling direction for future work. In the realm of practical applications, the proposed methodology holds promise for real-time sentiment tracking in social media discussions centered on literary works, offering a tool for understanding reader reactions and facilitating dynamic engagement. Overall, the study's comprehensive overview of sentiment analysis in literary texts lays the groundwork for future inquiries into the intricate interplay between language, narrative, and emotion.

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