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MACHINE LEARNING-BASED HUMAN RESOURCE MANAGEMENT INFORMATION RETRIEVAL AND CLASSIFICATION ALGORITHM

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Abstract. Efficient human resource management (HRM) is essential for company achievement in today's fast-paced corporate world. Businesses must find effective ways to retrieve and categorise the ever-growing amount of HR-related knowledge. This work presents a new method for retrieving and classifying HRM data using machine learning. Modern natural language processing (NLP) and CNN methods are used by the algorithm we developed to handle unorganized human resources (HR) information, including worker records, job postings, and certificates. HR decision-making is facilitated by the system's ability to derive insightful information from the information using sophisticated text mining and machine learning algorithms.The two main parts of the method are classification and data extraction. HR workers can more easily obtain the required knowledge thanks to information retrieval, which makes it possible to search HR data quickly and accurately. Contrarily, categorisation optimises the division of human resources information into pertinent classifications, including job positions, competencies, and achievement grades. We assess our algorithm's effectiveness on various datasets from actual HR datasets. The outcomes show how well our strategy works to streamline HRM procedures, cut down on manual labour, and increase the precision of decisions. Furthermore, our technology is compatible with corporate human resources offices and educational settings because it complies with worldwide university requirements.This study belongs to the growing body of knowledge in HRM. It provides a useful tool for businesses looking to improve employee relations, simplify HR procedures, and attract and retain talent. The suggested method is a valuable resource for academics and businesses alike because of its versatility and compliance with global educational norms.

Key words: Machine learning, human resource management, information retrieval, classification algorithm.

1. Introduction.

Humanity has become an invaluable resource that can do cognitive activities, regardless of harmful situations. Although in the twenty-first-century world of machines, human involvement is still necessary in many industrial processes [29]. Acknowledging the actions of others is now crucial for evaluating the accomplishments of every individual. These kinds of tasks can involve messy, prone to mistakes in human recordkeeping. Consequently, automatic identification methods have gained popularity and are now a topic of interest for the scientific community. Any unusual or suspect conduct among people will automatically set off an alarm that can be used to initiate personal intervention or self-improvement [23]. These days, automatic human activity detection is crucial to efficient and free of mistakes in institutions and manufacturing processes.

Recognition of activities and transfer learning have been examined independently in numerous research. However, only a small number of studies have examined activity recognition in transfer learning systems, and even fewer have discussed sensor-based HAR in transfer training augmented systems [31]. To the greatest extent of our ability, this is the final review paper that has been published that discusses HAR in the context of transfer learning. The same study from 2011 to 2021 is included in this publication, albeit it is mostly focused on HAR datasets and methods for categorisation [1]. The author thoroughly categorizes several HAR techniques according to their benefits and drawbacks to explore sensor-based and vision-based HAR. Similarly, the material is included in our paper, but it is in the transfer training system [24].

Human knowledge is required to carry out the extraction and selection of features in traditional machine learning algorithms. The responsibilities of picking and categorising features are distinct. Deep learning addresses the hole by employing only one step for recognition and categorisation to maximize the accuracy of the models. Whereas deep learning, machine learning demonstrates reduce the requirement for individual architectural features and dependency on outside resources because of autonomous training and the extraction of features [7, 11]. Furthermore, the main benefits of deep learning above conventional artificial intelligence

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approaches are its outstanding accuracy and end-to-end problem-solving capabilities, particularly when dealing with massive data sets like those used for recognizing speech, categorization of pictures, and phishing detection [8, 9, 2, 12].

High levels of difficulty, a mixture of constant and discontinuous procedures, interconnected and interrelated activities, and fluctuations present challenges for decision-makers in the management of supply chains (SCM), necessitating flexibility. One interesting potential answer to these problems is Reinforcement Learning (RL), an area of machine learning systems that specializes in making decisions in reverse. RL may serve as an adaptable regulator in these complex structures by figuring out how to behave in a way that maximizes the benefit as time passes [13, 33]. This kind of administrator, sometimes referred to as RL agent learns the best management behaviours for the complicated system in each possible state in order to achieve the greatest long-term systems objectives. [6, 10].

This study is driven by the pressing need to improve and modernize Human Resource Management (HRM) procedures in light of the quickly changing business environment of today. Employers are finding it more and more difficult to handle the volume of HR-related data that is always growing. This data includes but is not limited to, personnel files, job listings, and professional certifications. Even though this data is crucial for making strategic decisions, it is frequently in unstructured formats, which makes it challenging to locate, handle, and evaluate efficiently [28].

The conventional approaches to managing HR data are shown to be insufficient; they frequently involve a great deal of human labour that is laborious and error-prone. This inefficiency can make it more difficult for a business to react quickly to HR issues, which can hurt its overall competitiveness and performance.

The following is the suggested technique's primary contributions:

1. Algorithms using natural language processing (NLP) are excellent at collecting pertinent data from resumes, including educational background, abilities, and work experience, which automates the first screening step.
2. NLP approaches offer an improved comprehension of applicant capabilities by identifying and classifying skills and competences from textual information.
3. NLP and CNN can assist develop models of prediction that foresee employee turnover by examining trends in employee information and feedback. This would enable HR to take steps to solve retention difficulties.
4. To promote inclusion and diversity, NLP algorithms can assist in locating and reducing inequalities in job postings, performance appraisals, and other HR-related materials.

The remainder of our research paper is composed as follows: The relevant research on deep learning techniques, data retrieval, and human resource management is covered in Section 2. The suggested work's fundamental operating technique and algorithmic procedure are illustrated in Section 3. The outcomes and application of the suggested approach are assessed in Section 4. The job is concluded and the outcome evaluation is covered in Section 5.

2. Related Works. A systematic review technique is needed to outline the present state of the art for RL in SCM. The writer outlines various review techniques based on the goals of the investigation and the field of study [5]. The most appropriate type of evaluation in this situation is semi-systematic, which combines qualitative and quantitative techniques. If an issue is not well defined and has been extensively researched in several study fields of study, a semi-systematic evaluation of the literature is helpful. To provide a plan for future study, it attempts to convey the state of the art generally and its current uses [4].

It's difficult to choose the right approach for every kind of application. When hackers change their hacking techniques to exploit vulnerabilities in networks and customers' indifference, the model's precision and effectiveness would eventually degrade if the incorrect approach or methodology were employed [14]. To protect consumers against phishing assaults and detect phishing threats early, a plethora of phishing prevention solutions has been created.Throughout a range of businesses, deep learning-based security techniques are becoming increasingly popular in the fight against new phishing attacks [15, 16].

It was determined how well various machine learning (ML) methods could identify MQTT-based assaults [17]. The study evaluated three distinct levels of abstraction for packet-based, unidirectional in nature and bidirectional flowing aspects. The instruction and evaluation procedures made use of a MQTT generated database. The results of the experiment demonstrated that the proposed ML models were adequate to meet the IDS requirements of MQTT-based systems. Furthermore, the findings demonstrate that, whereas packet-based features are sufficient for most networked assaults, flow-based qualities are crucial for distinguishing MQTT-based attacks from innocuous data. According to the findings, the simulation has the greatest precision, at 99.04%. Two popular malware detection information sets, KDDCup99 and NSLKDD, were used in the investigation by the writer [18].

Translating and query-document screening are the two sections that make up CLIR. Severalapproachoccupiesrequest translation into the native tongue of the information gathering, followed by relevance determination using a single-language matched engine. One possible method for completing the translation process is statistically automated translation (SMT) [19] or neural machine translation (NMT) [26]. Although translating an item and matching it in a different language in a shared illustration space is a common two-step process, there is now an option to skip the translating step thanks to the development of bilingual word pictures [35] and multilingual already trained modelling languages. When adjusted, multinational pre-trained speech systems' word representations have context using the subsequent words in the order, making them useful for a variety of applications, particularly CLIR [20, 3].

A two-step process is employed by [21] to differentiate between benign and malicious nodes. In the first the stage, data is gathered by designated sniffing devices (DSs), after which the CCI is formed and routinely transmitted to the super node (SN) [22]. The SN then uses a regression approach on the gathered CCIs from various DSs in the following stage to differentiate between malicious and benign nodes. For multiple extreme situations in the network (GM), the detection characterisation is demonstrated using two movement models: Gauss Markov and random waypoint (RWP) [25]. Two dangerous techniques used in the workplace include distributed denial of service (DDoS) attacks and the black vortex.

Multiple sectors, including self-driving cars, recognizing faces, and medical equipment are using applications for deep learning. By learning by doing, deep learning teaches robots to function similarly to human brains [27]. Moreover, a computer model may automatically acquire the ability to do tasks like classification using massive datasets that contain text, audio, and pictures via the method of known as "deep learning." Models developed using deep learning can produce outcomes that are better than human beings in certain cases. Large amounts of data with labels, powerful computers, and multi-layered neural network designs are needed for training algorithms using deep learning [30, 32].Because algorithms using deep learning are so strong, scientists have been able to gather characteristics for URL classification and use these characteristics to suggest a variety of strategies for combating websites that are phishing [34].

3. Proposed Methodology. There are several essential elements in developing a technique for an information retrieving and classification method for human resource management (HRM) based on machine learning (ML). This approach will be designed to satisfy global academic requirements and be appropriate for an educational institution project in an area such as computer science or accounting management.Initially, the HR data is collected from the data source, next the data is pre-processed. After cleaning the data, normalization and feature engineering process is carried out. Next, the machine learning method Natural Language Processing (NLP) and the data is trained using CNN. The suggested method's architecture is depicted in figure 3.1.

3.1. Data Collection and Pre-processing. The open-sourcedataset is gathered from Kaggle, the HR dataset contains the details about the employee. The collected dataset is pre-processed by identifying missing values, duplicate records, and inconsistencies.

1. *Incomplete Values:* Find and fix any information that is incomplete. Among the options are removing columns or rows that have values that are absent. Use predictive modelling or methods of statistics (mean, median, mode) to impute values that are missing.
2. *Duplicated Documents:* To guarantee data integrity, look for and eliminate any entries that are duplicates.
3. *Inconsistencies:* Fix data entry errors, such as different date types or category variable types.

3.2. Normalization and Feature Engineering. In this work, min-max normalization method is used for normalizing the dataset.

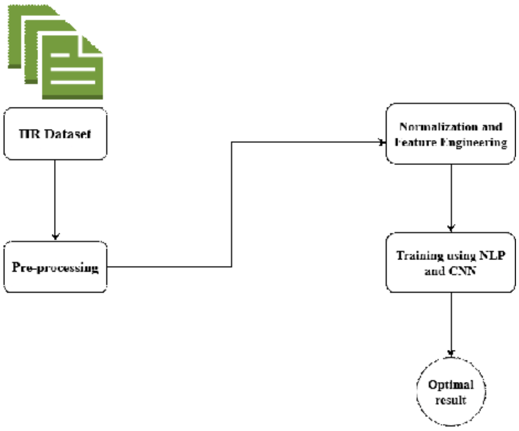

Fig. 3.1: Architecture of Proposed Method

3.2.1. Min-max normalization. Using a set range, often 0 to 1, this approach scales the characteristics. The process involves deducting the feature's minimal price and splitting the outcome by the feature's value.

$$min - max = \frac{x - \min?(x)}{\max{(x)\}} - \min?(x)} \tag{3.1}$$

Perfect for needs involving values within a restricted interval. It is susceptible to outliers, though.

3.2.2. Feature Engineering. A crucial stage in getting Human Resources (HR) data ready for predictive analytics and machine learning is feature design. To enhance the efficiency of artificial intelligence models, it entails adding new features or changing ones that already exist. Feature engineering is useful in HR data contexts to identify trends and conclusions which are not initially obvious. This in-depth method is appropriate for an undergraduate project in data science, accounting for managers, or HR management.

Recognize the characteristics that are currently present in the dataset, including tenure, pay, employment role, age, gender, and work evaluations. Recognize the features that are currently present in the data set, including tenure, pay, employment position, age, gender, and work evaluations. Compose characteristics that are composites of the current data points. For example, incorporating wages, incentives, and other benefits to create a feature called "total compensation." Create categorical bins from constant variables. For instance, tenure groups or age groupings. If two or more current features interact and could have an overall influence on the target variable, create new features based on these relationships.

3.3. Training the Dataset using Machine Learning method. There are multiple processes involved in developing a machine learning algorithm using HR retrieving information, from data preparation to model assessment of performance. The development of an algorithm that can precisely retrieve and categorize HR-related data depends on this procedure. This systematic method is appropriate for an educational project in data science or accounting management.

3.3.1. Natural language processing (NLP). Utilizing computational methods for understanding, interpreting, and modify human speech that exists in HR data is known as natural language processing, or NLP. NLP canclean information through unorganized textual information, that is frequently found in HR records and correspondence.

1. Resume processing and connecting refers to the process of automatically gathering relevant data (such as training, expertise, and abilities) from applications and comparing it to job specifications or position criteria.

2. **Feedback from Workers Evaluation:** Examining survey results, evaluations of performance, and feedback from workers to determine sentiment, spot common patterns, and comprehend the level of engagement and spirits among staff members.
3. **Job Application Optimization** is the process of Examining job posts and specifications to make sure that they're accessible, efficient, and aimed at the right people.
4. **Employment & Recruiting:** By finding those with the greatest potential through their online profiles and previous employment, NLP is used to screen applicants, match them with appropriate opportunities, and improve the hiring process.
5. **Employees Assistance and Bots:** Using natural language processing (NLP), chatbots are being used to provide data, respond to employee questions, and help with a variety of HR tasks.

3.3.2. Convolution Neural Network (CNN). The Convolutional neural networks, or CNNs, are a novel method intended for retrieving HR data; this is especially useful for complicated and organized data. Because of their propensity to identify trends and characteristics in geographic information, CNNs have long been recognized for their excellence in picture processing as well as analysis. But by considering textual as a type of data sequence with spatial links, they can be applied as well to organized written information in HR, such as applications, descriptions of jobs, and additionally organized feedback surveys.

Information is expressed numerically before being fed into a CNN, usually as embeddings (e.g., word embedded data). Language connections and semantic data are captured by these embedded data. the primary element of CNNs. These kinds of layers generate maps of features by filtering the input. Such filters can be used to slide over words embedded in text to identify trends or characteristics, such as specific words or mixtures of words that may point to HR-related characteristics. By combining characteristics, these layers lessen the dimension of the data while keeping the most important data—such as the existence of critical abilities or achievements on a CV.

Organize text data to preserve its context and sequence by converting it into an appropriate format, such as word embeddings. Create the CNN's layers, making sure to include pooling and convolutional layering with the right filter sizes. Depending on the dataset and task difficulty, the structure may change. Utilizing labelled HR information to educate the CNN. A properly labeled database that appropriately reflects the many groups or results you're attempting to forecast or obtain is crucial. To enhance the execution of the method, play around with numerous hyperparameters such as the number of layers, filter sizes, and number of filtering.

Convolutional Neural Networks (CNNs) are critical to the advancement of smart technologies due to their outstanding efficacy when conducting large-scale computations involving data. CNNs excel at spotting traits and patterns in pictures, which is why image categorization is one of their preferred applications. CNNs are employed in computerized systems to detect objects, circumstances, or irregularities in images acquired by photographers or other sensor types. Smart surveillance devices use CNNs to swiftly categorize and determine objects or persons. CNNs provide empirical information on the relative positions of elements in images, making it easier to recognize and locate them. CNNs are utilized by smart gadgets, such as self-driving automobiles, to swiftly identify others, vehicles that move, and obstacles.

A convolutional neural network is an instance of feedforward neural network that uses convolution processing and has a deeper architecture. This fundamental machine learning algorithm has numerous uses in computer vision, voice interpretation, image categorization, and other disciplines. A CNN, or "understanding coherent artificial neural system," can analyze and identify data based on its hierarchical organization.CNN consists of three important parts: its convolution layers the pooling layer, and the fully connected layer. Following features are extracted given the source information, the layer of convolution is frequently used to generate the characteristic mapping. The attribute is then down filtered utilizing the pooling layer, which reduces its size and computation cost. The resultant information obtained from the layer before it eventually gets transmitted to the completely linked layer, which creates a vector with one dimension of characteristics.

The beginning of the convolution stack has a pooling layer of roughly $1 * 2 * 2$, and a convolution kernel that is about $22 * 3 * 3$. In the final 2 conversion collections, the combination of pooling and convolution layers have sizes of $1 * 1 * 1$. The RELU activation procedure is used in all convolution layers, and serial normalizing is used to improve generalization ability, reduce unnecessary appropriate, and speed up training. Figure 3.2 illustrates the basic structure of CNN.

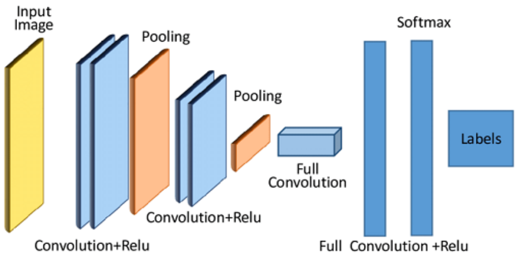

Fig. 3.2: Design of CNN

3.3.3. NLP with CNN. Transforming text into a format that CNNs can understand is the first step. Typically, this entails converting words or characters into dense vector representations called embeddings that capture the text's semantic qualities. Word embeddings are either directly learned during CNN training or come from pre-trained models such as Word2Vec and GloVe. Instead of sliding over image pixels, convolutional filters are used in natural language processing (NLP) to overlay word embeddings or character embeddings. These filters are intended to pick up on the syntactical patterns and local dependencies found in the text, such as phrases or brief word sequences with distinct meanings. The process generates a number of feature maps that show various elements of the text, such as the existence of particular words, phrases, or grammatical constructions.

After convolution, pooling layers are applied to reduce the dimensionality of the feature maps. This step helps to decrease the computational load and also to extract more global features from the text. Max pooling is the most common technique used, where the highest value in each region of the feature map is kept, capturing the most prominent features detected by the convolutions. After being flattened, the output from the pooling levels is routed through one or more fully linked layers. These layers perform the final task, which can be any NLP task, such as categorizing a sentence's sentiment or determining a document's categorization by combining the characteristics extracted by the convolutions and poolings. The last layer outputs the probabilities for each class using a softmax activation function for classification tasks.

4. Result Analysis. The proposed methodology for retrieving human resource management information using NLP-CNN. In this work the open-source dataset is gathered from Kaggle. It consists of employee details for evaluation. The evaluation metrics such as accuracy, precision, recall and f1-score.

A systematic method must be taken to assess the correctness of a Human Resources (HR) data retrieval systems that makes use of convolutional neural networks (CNNs) and natural language processing (NLP). This procedure entails putting the system in place, generating forecasts, and figuring out the accuracy. Considering the model's structure and the HR problem at hand is crucial, as employing CNNs in NLP tasks can be complicated.

Convolutional Neural Networks (CNNs) can be useful for retrieving HR data, particularly when handling complex structured data or unstructured data such as photographs (e.g., personnel photos, document scans). It is less typical, nevertheless, with conventional, tabulated HR data. The main uses of CNNs are in the processing of images and visual applications. A CNN might be useful if your HR data retrieval requirement calls for processing such image-based information.

Create an CNN design that works for the job at hand. Selecting the quantity of filters, pooling layers, kernel size, convolutional layers, and fully connected layers is required. Utilize the training set to hone your CNN. To be sure that the model is learning—that is, reducing loss and raising correctness on the validation and training sets—keep an eye on the training procedure. Accuracy is a typical statistic for classification jobs. It is the percentage of cases among all instances that were accurately anticipated. Change hyperparameters like the quantity of times and the quantity of batches and learning rate. To predict whether the algorithm will perform on fresh, untested data, assess its efficacy on the test set. Examine instances wherein the example has made mistakes to learn from them and find areas for development. In figure 4.1 shows the result of accuracy.

When assessing a Convolutional Neural Network (CNN) model's accuracy in relation to HR data, it's

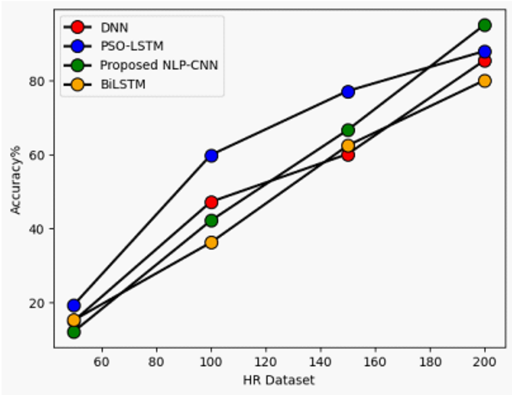

Fig. 4.1: Accuracy

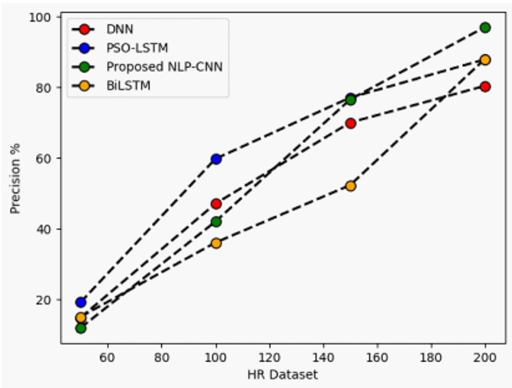

Fig. 4.2: Precision

important to comprehend the context of the issue, the characteristics of the HR dataset, and the computation and interpretation of precision as a metric. The proportion of correctly forecast positive findings precision refers to the overall total of projected positives. It's a crucial measure for issues with classification. Identify the HR issue that you are trying to solve with CNN (such as sentiment evaluation from employee feedback, resume screening, or staff attrition prediction). HR information frequently have imbalanced classes (e.g., a small percentage of departing employees relative to those remaining). In these kinds of situations, accuracy is especially crucial to predicting the positive class—that is, the individuals who are expected to depart. In figure 4.2 shows the result of precision.

It is necessary to know how to assess a Convolutional Neural Network's (CNN) effectiveness while using it for HR data, especially when it comes to tasks like document categorization or image-based worker information analytics. Recall is one of the most important parameters for this. In the context of employing CNNs for HR data, let's examine recall and its computation and interpretation. shows that the model does a decent job of identifying the favorable cases. This could entail correctly identifying most pertinent papers or information about workers in HR. implies that a sizable portion of positive cases may be absent from the model. This could be an issue in situations like missing important documents or misunderstanding personnel data, when missing positive examples can have detrimental effects.

Recall and precision—the capacity of a model to recognize only pertinent items—often represent trade-offs. Recall optimization may result in more false positives. In HR, you might give recall a higher priority than precision, or vice versa, depending on the assignment. For example, excellent recall may be particularly crucial

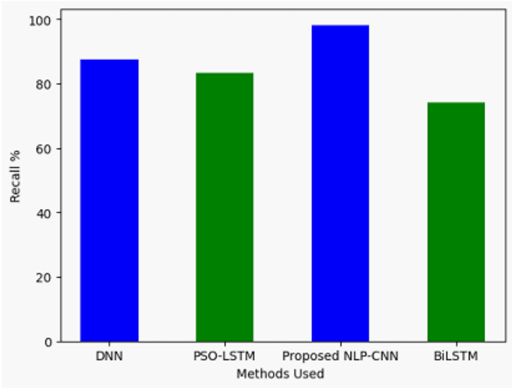

Fig. 4.3: Recall

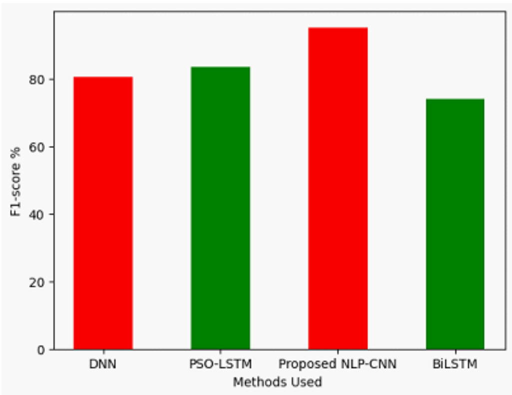

Fig. 4.4: F1-Score

in a legal file search to make sure no key item is overlooked. Recall is a vital indicator of performance when assessing a CNN's effectiveness in HR-related tasks, particularly when it comes to accurately identifying many pertinent cases. Efficient assessment of models and deployment require striking a balance between recall and other measures, as well as considering the circumstances and consequences of its use in HR. In figure 4.3 shows the result of recall.

A common measure used for assessing how well a model developed using machine learning performs, especially in the field of classification, is the F1-score. It is particularly pertinent in situations when the intended class allocation is unbalanced or anywhere the effect of false positives and false negatives is substantial, as is frequently the case with HR-related data. Create a CNN architecture that works with the HR data. Layers, functions for activation, and the result layer for categorization are all defined in this way. Utilizing a suitable optimization, loss function (such as binary cross-entropy for binary categorization), and metrics (such as precision and recall), build the framework. Make sure to utilize a validation set to track performance as you train your model on the learning set. Figure 4.4 depicts the outcome of the f1-score.

5. Conclusion. Effective human resource management (HRM) is critical to business success in today's hectic corporate environment. Companies need to come up with efficient methods for retrieving and classifying the continually expanding body of HR-related knowledge. This article presents a unique machine learning-based method for obtaining and classifying HRM information. Our techniqueforces state-of-the-art natural language processing (NLP) and CNN techniques to manage disorganized human resources (HR) data, such as employee records, job advertisements, and certificates. The system's capacity to extract relevant details from data using advanced text analysis and machine learning techniques facilitates HR decision-making.The method consists of two primary components: extraction of information and categorization. Data extraction, which enables fast and precise searches of HR data, helps HR professionals get the knowledge they need more readily. On the other hand, classification maximizes the separation of data related to human resources into relevant categories, such as job roles, skill levels, and performance levels. We evaluate the performance of our system on multiple datasets extracted from real-world HR databases. The outcomes show the success of our strategy in streamlining HRM processes, reducing manual labor, and improving decision precision. Additionally, because our technology satisfies international university regulations, it may be used in both corporate HR departments and educational contexts.This research adds to the expanding body of information in HRM and offers a helpful resource for companies trying to enhance employee relations, streamline HR processes, and draw and retain talents. The proposed approach's adaptability and adherence to international educational standards make it a useful tool for both academia and industry. The proposed approach's adaptability and adherence to international educational standards make it a useful tool for both academia and industry. In future, complex dataset and deep learning models will be used in human resource management.

REFERENCES

[1] S. Ahmadi, *Optimizing data warehousing performance through machine learning algorithms in the cloud*, International Journal of Science and Research (IJSR), 12 (2023), pp. 1859–1867.

[2] M. A. U. Alam, M. M. Rahman, and J. Q. Widberg, *Palmar: Towards adaptive multi-inhabitant activity recognition in point-cloud technology*, in IEEE INFOCOM 2021-IEEE Conference on Computer Communications, IEEE, 2021, pp. 1–10.

[3] O. Alkadi, N. Moustafa, B. Turnbull, and K.-K. R. Choo, *A deep blockchain framework-enabled collaborative intrusion detection for protecting iot and cloud networks*, IEEE Internet of Things Journal, 8 (2020), pp. 9463–9472.

[4] S. Alqahtani, G. Lalwani, Y. Zhang, S. Romeo, and S. Mansour, *Using optimal transport as alignment objective for fine-tuning multilingual contextualized embeddings*, arXiv preprint arXiv:2110.02887, (2021).

[5] Y. A. Alsariera, V. E. Adeyemo, A. O. Balogun, and A. K. Alazzawi, *Ai meta-learners and extra-trees algorithm for the detection of phishing websites*, IEEE access, 8 (2020), pp. 142532–142542.

[6] Y. A. Alsariera, A. V. Elijah, and A. O. Balogun, *Phishing website detection: forest by penalizing attributes algorithm and its enhanced variations*, Arabian Journal for Science and Engineering, 45 (2020), pp. 10459–10470.

[7] Z. Alshingiti, R. Alaqel, J. Al-Muhtadi, Q. E. U. Haq, K. Saleem, and M. H. Faheem, *A deep learning-based phishing detection system using cnn, lstm, and lstm-cnn*, Electronics, 12 (2023), p. 232.

[8] S. An, G. Bhat, S. Gumussoy, and U. Ogras, *Transfer learning for human activity recognition using representational analysis of neural networks*, ACM Transactions on Computing for Healthcare, 4 (2023), pp. 1–21.

[9] K. Anand, S. Urolagin, and R. K. Mishra, *How does hand gestures in videos impact social media engagement-insights based on deep learning*, International Journal of Information Management Data Insights, 1 (2021), p. 100036.

[10] S. Anbukkarasi, V. E. Sathishkumar, C. Dhivyaa, and J. Cho, *Enhanced feature model based hybrid neural network for text detection on signboard, billboard and news tickers*, IEEE Access, (2023).

[11] C. Anilkumar, S. Lenka, N. Neelima, and V. Sathishkumar, *A secure method of communication through bb84 protocol in quantum key distribution*, Scalable Computing: Practice and Experience, 25 (2024), pp. 21–33.

[12] N. Aslam and M. H. Kolekar, *Unsupervised anomalous event detection in videos using spatio-temporal inter-fused autoencoder*, Multimedia Tools and Applications, 81 (2022), pp. 42457–42482.

[13] A. Basit, M. Zafar, X. Liu, A. R. Javed, Z. Jalil, and K. Kifayat, *A comprehensive survey of ai-enabled phishing attacks detection techniques*, Telecommunication Systems, 76 (2021), pp. 139–154.

[14] H. Bonab, J. Allan, and R. Sitaraman, *Simulating clir translation resource scarcity using high-resource languages*, in Proceedings of the 2019 ACM SIGIR International Conference on Theory of Information Retrieval, 2019, pp. 129–136.

[15] H. Bonab, S. M. Sarwar, and J. Allan, *Training effective neural clir by bridging the translation gap*, in Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, 2020, pp. 9–18.

[16] L. Bonifacio, V. Jeronymo, H. Q. Abonizio, I. Campiotti, M. Fadaee, R. Lotufo, and R. Nogueira, *mmarco: A multilingual version of the ms marco passage ranking dataset*, arXiv preprint arXiv:2108.13897, (2021).

[17] M. Braschler, *Clef 2002—overview of results*, in Workshop of the Cross-Language Evaluation Forum for European Languages, Springer, 2002, pp. 9–27.

[18] L. Chen, Y. Zhang, R. Zhang, C. Tao, Z. Gan, H. Zhang, B. Li, D. Shen, C. Chen, and L. Carin, *Improving sequence-to-sequence learning via optimal transport*, arXiv preprint arXiv:1901.06283, (2019).

[19] A. Conneau, K. Khandelwal, N. Goyal, V. Chaudhary, G. Wenzek, F. Guzmán, E. Grave, M. Ott, L. Zettlemoyer, and V. Stoyanov, *Unsupervised cross-lingual representation learning at scale*, arXiv preprint arXiv:1911.02116, (2019).

[20] M. A. Ferrag and L. Maglaras, *Deepcoin: A novel deep learning and blockchain-based energy exchange framework for smart grids*, IEEE Transactions on Engineering Management, 67 (2019), pp. 1285–1297.

[21] S. Hosseini and D. Ivanov, *A multi-layer bayesian network method for supply chain disruption modelling in the wake of the covid-19 pandemic*, International Journal of Production Research, 60 (2022), pp. 5258–5276.

[22] H. Huang and X. Tan, *Application of reinforcement learning algorithm in delivery order system under supply chain*

environment, Mobile Information Systems, 2021 (2021), pp. 1–11.

[23] Z. Huang, P. Yu, and J. Allan, *Improving cross-lingual information retrieval on low-resource languages via optimal transport distillation*, in Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining, 2023, pp. 1048–1056.

[24] D. Musleh, M. Alotaibi, F. Alhaidari, A. Rahman, and R. M. Mohammad, *Intrusion detection system using feature extraction with machine learning algorithms in iot*, Journal of Sensor and Actuator Networks, 12 (2023), p. 29.

[25] T. T. Nguyen and A. T. Luu, *Improving neural cross-lingual abstractive summarization via employing optimal transport distance for knowledge distillation*, in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 36, 2022, pp. 11103–11111.

[26] W. O'Sullivan, K.-K. R. Choo, and N.-A. Le-Khac, *Defending iot devices from malware*, Cyber and Digital Forensic Investigations: A Law Enforcement Practitioner's Perspective, (2020), pp. 5–29.

[27] L. Qin, M. Ni, Y. Zhang, and W. Che, *Cosda-ml: Multi-lingual code-switching data augmentation for zero-shot cross-lingual nlp*, arXiv preprint arXiv:2006.06402, (2020).

[28] R. Rajalaxmi, M. Saradha, S. Fathima, V. Sathish Kumar, M. Sandeep Kumar, and J. Prabhu, *An improved mangonet architecture using harris hawks optimization for fruit classification with uncertainty estimation*, Journal of Uncertain Systems, 16 (2023), p. 2242006.

[29] A. Ray, M. H. Kolekar, R. Balasubramanian, and A. Hafiane, *Transfer learning enhanced vision-based human activity recognition: a decade-long analysis*, International Journal of Information Management Data Insights, 3 (2023), p. 100142.

[30] N. Reimers and I. Gurevych, *Making monolingual sentence embeddings multilingual using knowledge distillation*, arXiv preprint arXiv:2004.09813, (2020).

[31] B. Rolf, I. Jackson, M. Müller, S. Lang, T. Reggelin, and D. Ivanov, *A review on reinforcement learning algorithms and applications in supply chain management*, International Journal of Production Research, 61 (2023), pp. 7151–7179.

[32] S. Saleh and P. Pecina, *Document translation vs. query translation for cross-lingual information retrieval in the medical domain*, in Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, 2020, pp. 6849–6860.

[33] S. Saravanan, V. Sathishkumar, N. Rajalakshmi, R. Sukumar, and V. Muthukumaran, *Prediction and classification of skin melanoma cancer using active hybrid machine learning technique*, in Journal of Physics: Conference Series, vol. 2580, IOP Publishing, 2023, p. 012039.

[34] N. Thapa, Z. Liu, D. B. Kc, B. Gokaraju, and K. Roy, *Comparison of machine learning and deep learning models for network intrusion detection systems*, Future Internet, 12 (2020), p. 167.

[35] H. Wu, H. Han, X. Wang, and S. Sun, *Research on artificial intelligence enhancing internet of things security: A survey*, Ieee Access, 8 (2020), pp. 153826–153848.

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