Analyzing the Concept of 'One Nation, One Law' in India: A Machine Learning Approach to Legal Texts and Public Opinion

Dr. Zahid Parwez,
Asst. Professor,
Xavier Law School, XIM University,
Odisha-752050, Mail: zahid@xim.edu.in
https://orcid.org/0000-0001-7511-0624

Abstract

One Nation, One Law has been the subject of heated controversy in political India's and legal spheres, with many questioning whether or not the country needs a set of universal civil laws that would apply regardless of a person's religion, region, or culture. To examine judicial rulings, public discourse, and legal texts pertaining to the Uniform Civil Code (UCC) and associated reforms, this chapter uses a unique multidisciplinary approach that incorporates ML techniques. The research shows that public mood is changing, that there are repeating themes, and that there are geographical differences in opinion by using topic modelling, sentiment analysis, Natural Language Processing (NLP), and datasets that include social media content and legal documents. The results point to a complicated interaction between modern pluralistic identities, political narratives, and constitutional duties. The internet conversation surrounding One Nation, One Law and its perceived ramifications on social justice, secularism, and national integration yield fresh insights as they apply ML.

Keywords: Uniform Civil Code (UCC), Natural Language Processing (NLP), Independent Component Analysis (ICA).

I. INTRODUCTION

The One Nation, One Law approach can be better understood by looking at the relevant federal and state laws that deal with education. Part of this process involves looking at regulations that govern things like school buildings required courses of study and the credentials of educators. If we want to know where the policy stands legally and where it might be lacking or in need of modification it needs to look no further than these legislative acts. Numerous obstacles arise while attempting to put the One Nation, One Law policy into action [1]. Inequalities in socioeconomic status impact students' ability to pay for a good education dealing with cultural diversity requires empathy and understanding and there may be pushbacks because of concerns about regional autonomy and competing local agendas [2]. There needs to be a sophisticated strategy for implementing policies in light of the fact that there is opposition from many sectors including political bodies and educational institutions. A well-rounded approach that values regional variation while aiming for national consistency is necessary to tackle these difficulties. To sum up the One Nation, One Law program is a revolutionary attempt to standardize education in India with the goal of providing every child with an equal opportunity to acquire a high-quality education [3]. It is possible that this strategy will have a major influence on the Indian educational system if it takes into account constitutional rights uses legislative and judicial frameworks and deals with the intricacies of socio-economic and regional concerns.

An in-depth examination of how this policy can change the face of education in India is laid out in the introduction which aims to make all students' educational experiences more equal and unified. Although it's true that India is now considered a nation-state the current global political climate means that this status did not exist before or after independence hence the one nation, one law debate has its roots in the idea that India is a nation-state [4]. Hindi is being promoted which is really a euphemism for being coerced and this has been at the Centre of the country's linguistic controversy as of late. There would be a new kind of imperialism if a specific language were forced on all of India. The India is seeking a corpus of substantive civil law that would be based on English law but would become Indian

law on the subjects it addressed once passed [5]. We finally believe that India would greatly benefit from such a codification of laws which should be meticulously crafted while keeping in mind the countries unique circumstances institutions and people's character religion and customs. Codification according to the Commission should not cover issues like the personal laws of Muslims and Hindus which are based on their faiths. A number of today's geopolitical tensions and disputes between nations and states have their origins in violent struggles and military conflicts. The One Nation, One Law scholarship aims to investigate these causes. Hybrid warfare tactics such as low-intensity warfare signature drone strikes extra-judicial executions covert assassination campaigns counterinsurgency operations, and foreign internal defense operations are being expanded by numerous regimes [6].

II. LITERATURE SURVEY

With a view toward meeting the demands of network public opinion analysis and crisis public opinion early warning in higher education this research examines the semantic sentiment analysis method. The majority of public opinion data is derived from brief text comments which have text that is decoupled from written language a simplified structure and no normatively [7]. Emotional dictionaries and feature extraction are common components of traditional sentiment analysis methodologies but due to the NLP of Internet culture technical assistance is required to update even the dictionaries [8]. An LSTM model is suggested to mine the DL properties of text accurately determining its emotional tendency based on the research and study of attention mechanisms and DL related technologies [9]. According to CNN and LSTM text processing the primary duties is as follows LSTM can efficiently extract global aspects of the sequence while retaining text history information while CNN can better extract local features of the text. In order to analyze campus reviews this study uses DL methods that are based on CNN. Emotional propensity classification using CNN improved classification performance compared to traditional SVM [10]. This was achieved after collecting campus hot topics for pre- processing and using the SVM model to generate word vectors. An improved text representation was achieved by the fusing of syntactic features in the LERT which was then bidirectional SRU embedded with a soft attention module to classify the attitudes users expressed in postings. The development of AI algorithm and DNN model generation and creation is art [11]. Models of NN such as the CNN the GAN and VAE allow generative models to understand and absorb abstract features like painting techniques and styles, from existing images making it easier to generate and create new images. In the realm of NLP sentiment analysis faces the problem of insufficient labeled data [12]. Since DL models are useful because of their DL potential sentiment analysis and DL approaches have been combined to overcome this issue [13]. This Review is a compilation of recent research on sentiment analysis issues and how DL models like CNNs and others have been used to address them. Many different areas of study come together in sentiment analysis making it a truly interdisciplinary area of study [14]. These areas include computational linguistics information retrieval and semantics NLP, AI and ML. There are distinct extraction levels that can be used to categorize sentiment analysis methodologies. Approaches to sentiment classification that rely on DT include KNN, CRF, HMM, SDC and SMO [15]. The DL has generated state-of-the-art results in numerous application fields including computer vision, speech recognition, NLP and more since it emerged as a powerful ML technique. The DL use to sentiment analysis categorization is enhanced by NN since they bring significant advances to NLP [16]. One pre-trained NN that outperforms competing sentiment categorization techniques is BERT. Among the many NLP tasks sentiment analysis also known as Opinion Mining automatically extracts subjective information from texts including views

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue2 (2025)

sentiments, evaluations, appraisals, attitudes and more [17]. Our main emphasis in this is on detecting the polarity of sentiments. We take a look at sentiment analysis and how DL is being used to determine sentiment polarity. Academics and students interested in the field of linguistics as a whole will find this review useful in their pursuit of a better understanding of DNN [18]. We hope that by doing this survey they will be able to determine which models have been the most successful thus far and come up with new directions to take sentimental analysis in terms of research. Furthermore, it failed to cover popular DL techniques such as GAN and DRL. Although they did touch on a technical review of DL for sentiment analysis omitted major variants

of DL techniques [19]. Because of this we are certain that this review will provide readers with a comprehensive understanding of current developments including new methods and studies in sentiment analysis that include DL approaches like GAN cognitive attention-based models DRL models and classical attention mechanisms [20].

III. METHODOLOGY

One school of thought holds that, short of major technological breakthroughs, artificial intelligence should not significantly impact the practice of law. The reasoning behind this is that practicing law is believed to necessitate higher-order cognitive talents, which are currently unattainable by AI technology. As an example, in situations where the law and facts are murky, solicitors often use a combination of abstract reasoning and problem-solving abilities. In contrast, current AI systems still lag far behind humans when it comes to complex cognitive processes like analogy reasoning, which are essential in the legal profession. These and other shortcomings of present AI systems lead one to believe that AI will not make a dent in the abstract and uncertain field of law until computers can mimic the higher-order thinking skills exhibited by experienced lawyers.

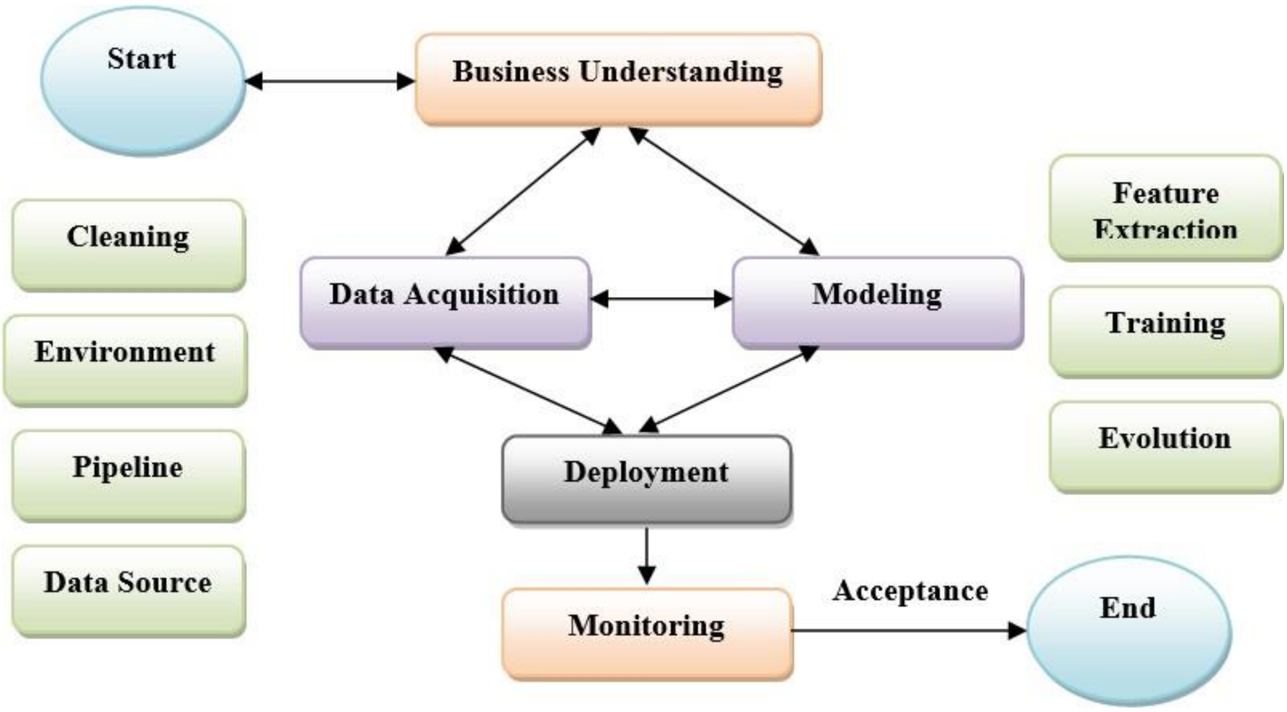

Fig. 1. Basic Architecture of ML

Machine learning, as shown in Figure 1, consists of a number of stages, including modelling, data acquisition and understanding, business comprehension, and implementation.

A. Preprocessing the Data:

The purpose of text preprocessing is to remove superfluous characteristics and extract relevant ones from text in order to make ML model creation more efficient and accurate. The feedback from individuals was tokenised sentence by sentence using delimiters such as semicolons, commas, colons, and periods. The tokens lack a specific sequence, and each represents a distinct concept. To ensure that the content maintains identical meaning in both lowercase and uppercase, all review text was converted to lowercase [21].

The absence of semantic significance in punctuation and its potential to introduce noise into data render its elimination a significant hurdle in NLP. Consequently, they omitted punctuation marks in our product evaluations. Because they didn't add much to understanding the data, the stop words were removed. Decreasing the text's depth makes patterns and meanings stand out more once stop words are removed, highlighting the important terms.

B. Extraction of Features:

By using an orthogonal transformation, PCA is able to separate linearly uncorrelated features from correlated data sets. The newly introduced characteristics with a size less than or equal to the original variables are called principal components. Because principal component analysis is not supervised, it does not require labelling. The main components are considered to be autonomous if the data follows a normal distribution [22]. PCA lowers the original variable count by removing final principal components that don't add much to the observed variability. By linearly modifying the data and decreasing redundancy, PCA aims to maximize information.

It finds the best number of k-dimensional orthogonal vectors for data description by using a small number of linear combinations to examine the variance-covariance patterns of a set of attributes. The initial derived feature, the principal component, is constructed with a descending order of contribution and represents the most significant proportion of variance in the original dataset. PCA is useful when numerous independent variables exhibit high correlation with each other. The major component guarantees a solution for any dataset due to its comprehensiveness and efficiency.

C. Training in the Model:

1) Supervised Learning:

The goal of supervised learning in ML is to learn a function that takes an input and returns an output by comparing it to previously trained examples of such functions. It uses a collection of training examples and labelled training data to infer a function. That type of system that relies on human oversight is known as a supervised ML algorithm. Both a training dataset and a test dataset are extracted from the input dataset. Predicting or classifying the train dataset's output variable is necessary. In order to make predictions or classifications on the test dataset, every algorithm learns patterns from the training dataset [23]. The algorithmic process of supervised machine learning. Here they have covered the most well-known supervised ML techniques.

a) DT:

In graph theory, a decision tree is a hierarchical representation of possible actions and their outcomes. In a decision-making graph, each node stands for an event or option, and each edge represents a rule or condition for making that choice. Every tree consists of nodes and branches. In a classification tree, each node represents an attribute within a set, while each branch signifies a potential value that the node may assume.

b) NB:

Assuming that predictors are independent, it is a classification method that is based on Bayes' Theorem. NB classifiers, in their simplest form, take it for granted that there is no correlation between the existence of one feature in a class and the existence of any other feature. The text categorization sector is primarily the focus of Naïve Bayes. Based on the conditional likelihood of occurrence, it is mostly employed for clustering and classification purposes.

Algorithm 1: NB Pseudo Code
Input: Dataset Training S.
$E = (e1, e2, e3, \dots, en)$
Output: A category of testing dataset.
Steps:
1. Examine the dataset training S.
2. Compute the mean and SD of the predictor variables for each class.
3. Reiterate Ensure the computation of the probability for each predictor variable $(e1, e2, e3, \dots, en)$ within each class utilizing the Gaussian density equation.
4. Determine the probability for each category;
5. Obtain the highest probability

c) SVM:

Another often-utilized advanced ML technology is the SVM. SVM in machine learning are supervised learning models accompanied by learning algorithms that evaluate data for classification and regression analysis. The kernel approach allows SVM) to efficiently do both linear and non-linear classification by implicitly mapping inputs into high-dimensional feature spaces. Separate the classes by drawing lines between them. The maximum distance between the margin and the classes is attained by positioning the margins to minimize classification error.

2) Unsupervised Learning:

a) ICA:

In cases when the factors are not normally distributed, ICA extends factor analysis to account for them. Many real-world datasets have structures that may be described as linear combinations of sparse sources, which makes this extension interesting. Images, audio, and biomedical signals (EEG, etc.) all fall under this category [24]. Assuming that the factors' distributions are non-Gaussian with a larger kurtosis than the mean is all that is required to define sparsity. A sparse distribution would have a bigger peak at zero and heavier tails compared to a normal distribution with the same mean and variance, as shown by $o(w) = \frac{\beta}{2}\exp\{-\beta|w|\}$.

Multiple cost function training neural networks can be used to create models such as PCA, FA, and ICA. Although it offers intriguing connections to biological information processing, it is unclear what benefit this implementation/interpretation has from a machine learning standpoint. As an alternative to ML estimation, Bayesian inference can be used to determine the parameters of probabilistic PCA, FA, and ICA.

b) K-means:

The subsequent text elucidates the close association between the Gaussian mixture model and the k-means clustering algorithm, which operates in an unsupervised manner. Let us assume momentarily that each Gaussian possesses a covariance matrix that is proportional to the identity matrix. For every $\sum_l = \mu^2 J, \forall l$, and $\gamma_l = 1/l, \forall l$. They will define EM, an iterative procedure, so that you can estimate the maximum likelihood parameters of this model. The k-means method is precisely what emerges when they reduce $\mu^2 \rightarrow 0$. Although k-means is clearly not a suitable model of the data it only contains singular Gaussians, it is sometimes justified when clustering data in order to minimize a distortion measure instead of constructing probabilistic models.

3) Hybrid Models:

Here, they'll have a look at the CNN and LSTM models side by side. In this research, it used two ML and DL models—to analyse the tone of case law. Conventional approaches, CNN, LSTM, and CNN-LSTM. Employing CNN and LSTM models to extract sentiment data from court papers is the key to this study's success [25].

a) CNN:

Specifically, CNN models excel at tasks that involve recognizing surrounding signs or traits due to their capacity to extract local patterns and features from text input. In legal documents, they are able to identify emotionally charged words, phrases, or clauses. Due to their capacity to swiftly learn local patterns by leveraging shared weights across several input areas, CNNs offer efficiency computational during training. Their remarkably short training period makes them ideal for large legal text collections. Here, CNN shine as potent feature extractors, capable of mining texts for useful information-like structures, patterns, or even individual words. Here, CNN shine as potent feature extractors, capable of mining texts for useful information-like structures, patterns, or even individual words.

b) The Model LSTM:

LSTM models are great for tasks that require comprehending the context and sequence of words in text input. When doing legal sentiment analysis, it is crucial to have a complete understanding of the intricate textual context. The complex web of relationships and nuanced sentiment patterns seen in legal

documents are ideal for LSTMs' degree of detail comprehension. LSTM models outnumber CNN models in terms of both complexity and the number of parameters. Nevertheless, they were able to reach impressive accuracy rates, which highlights their proficiency in analysing sentiment dynamics in Canadian maritime case law.

a) **CNN-LSTM:**

Over the course of fifty training epochs, this study used graphical representations of loss and accuracy metrics to evaluate the performance of CNN and LSTM models. The accuracy graph displays the model's data classification performance, while the loss graph displays its prediction precision. Along with this, the accuracy graph shows how well the model incorporates labels into opinions, and the loss graph shows how well it minimizes prediction mistakes. The SE visualizations contribute to the larger conversation around sentiment analysis in the legal field by making it easier to see how the model changed while training to incorporate documents from maritime case law in Canada.

IV. Results and Discussion

People have always been sceptical of the idea of using pure fiat money as a medium of exchange for goods and services, hence its widespread adoption was accompanied by numerous rejections and failures. As he characterized it in his influential work The Wealth of Nations, barter existed prior to the advent of money because it allowed people to trade goods and services without the need for a means of exchange like paper currency or coins. A number of nations are trying to reduce their current account and trade deficits by engaging in more barter transactions rather than using dollars. These countries are severely indebted and have little foreign reserves, and the United States has put sanctions on them.

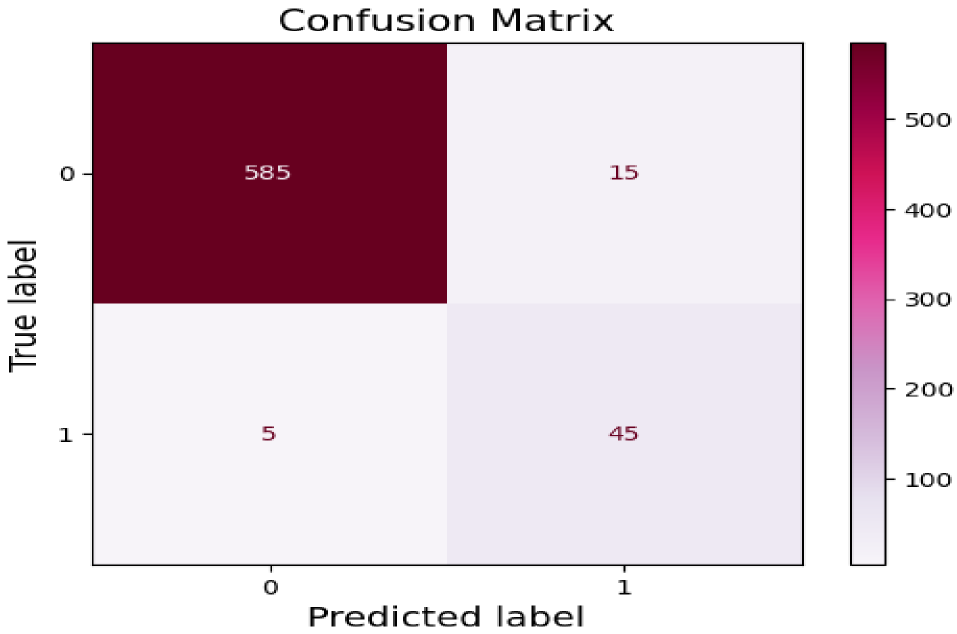

Fig. 1. **Confusion Matrix for Proposed Model**

A confusion matrix showing the results of a CNN-LSTM classification model is shown in the Figure 2. With few erroneous predictions in either way, this points to good classification performance, particularly when it comes to determining class 0. In general, the model is very accurate and has a nice mix of specificity and sensitivity.

TABLE I. **PROPOSED MODEL PERFORMANCE**

Models	**Accuracy**	**Precision**	**Recall**	**F1-Score**
DT-SVM	89.28	87.76	85.91	89.37
ICA-K-means	85.37	83.29	81.77	85.48
CNN-LSTM	**96.92**	**94.84**	**92.61**	**96.98**
CNN	90.78	88.21	86.11	90.82
LSTM	92.17	90.37	88.84	92.64

All five models' performance indicators are summarized in Table 1. The DT-SVM, ICA-K-means, CNN-LSTM, CNN, and LSTM models are all instances of such models. In most metrics, including Accuracy, Precision, Recall, and F1-Score, CNN-LSTM outperforms its competitors.

Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue2 (2025)

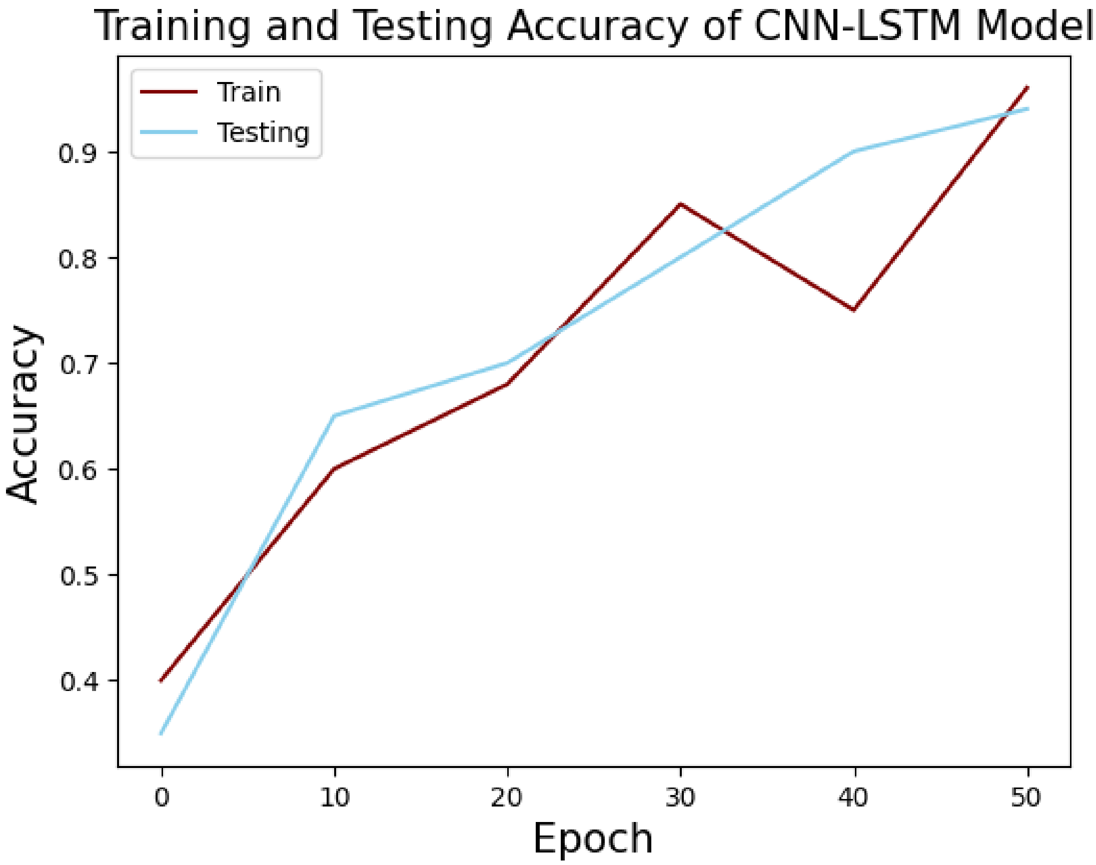

Fig. 2. **Training and Testing Accuracy of the Proposed Model**

Attack vs Iterations is a graphical representation of the correlation between iteration count and attack value. Attack numbers range from 11 to 18, while iterations range from 10 to 50 on the X-axis. Connected by a red line to emphasise the pattern, the red diamonds show particular attack values at different iterations. At 10 iterations, the attack value is 18, and by 30 iterations, it has decreased to 13. There is a small rise after 40 iterations, and then a last decrease to 11 at 50 iterations. This pattern indicates that the attack values generally get better or optimised with each iteration, with just minor variations along the way.

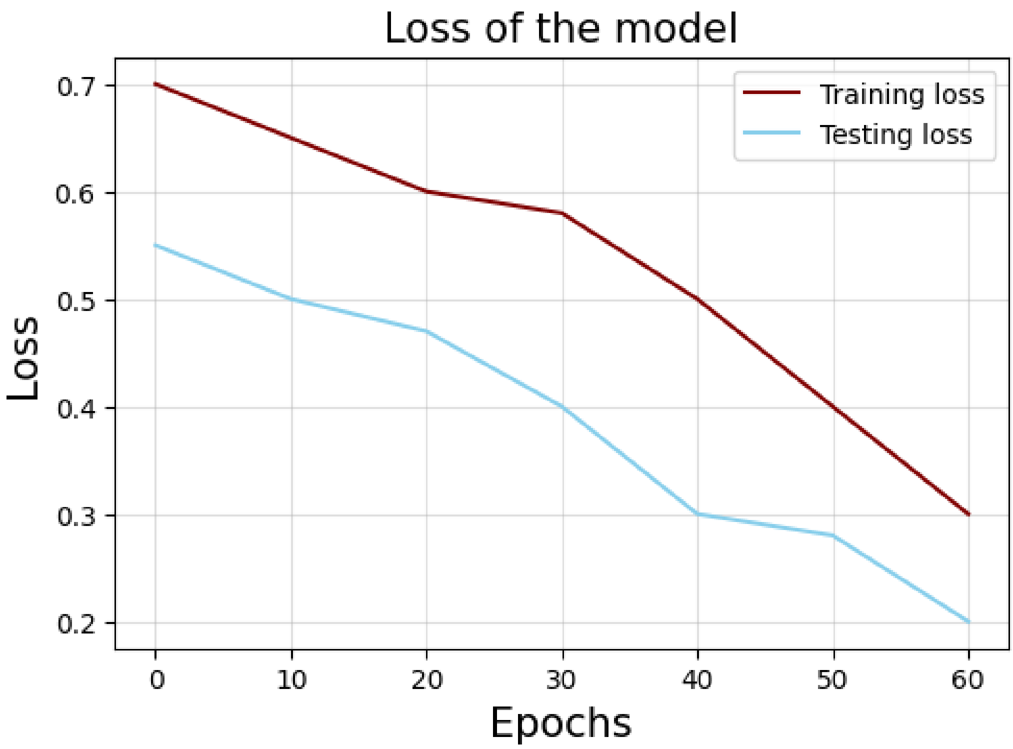

Fig. 3. **Training and Testing Loss of the proposed model**

Under Loss Proposed Model, the can see the training and testing losses over 60 Eproch. A model's training loss indicates how well it matches the taught data, whereas testing loss indicates its generalizability by measuring how well it performs on unknown data.

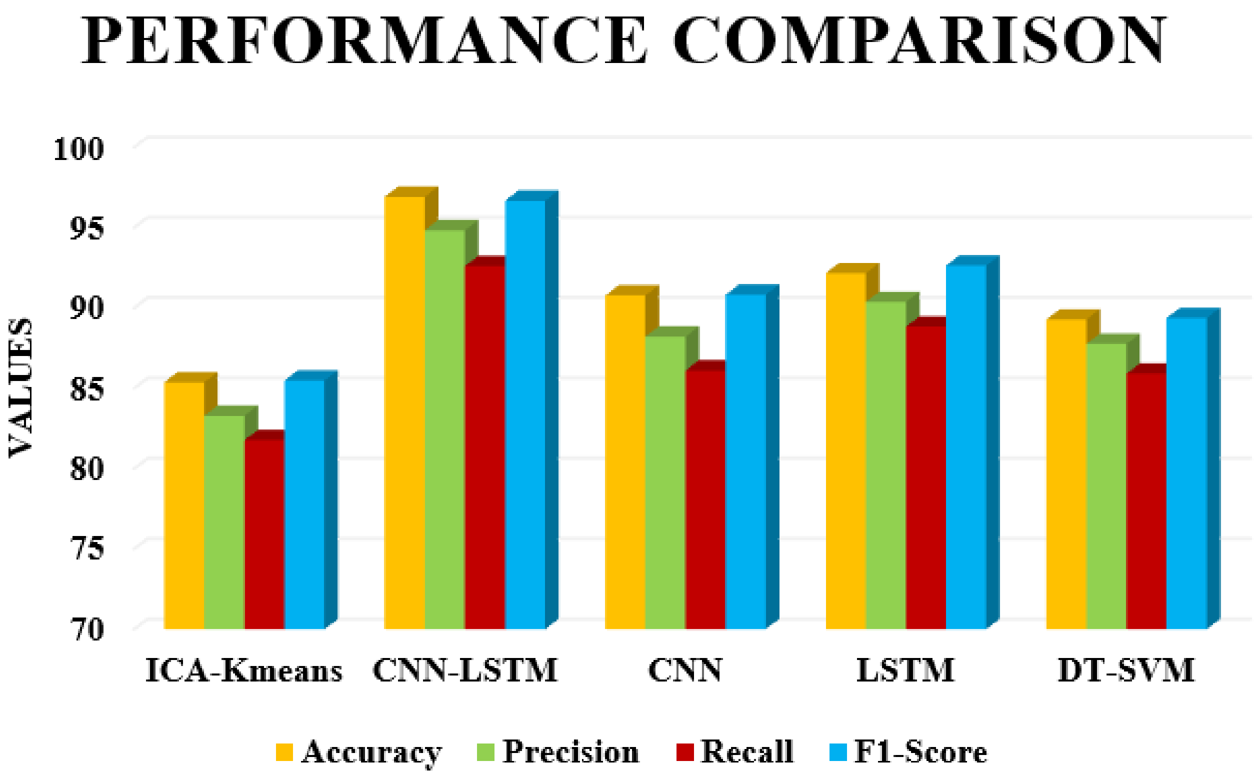

Fig. 4. **Proposed Model Performance Comparison**

The outcomes of a performance comparison of DT-SVM, ICA-Kmeans, CNN, LSTM, and

CNN-LSTM are displayed in this bar chart. In comparison to the other models, the CNN-LSTM algorithms perform the best.

V. Conclusion and Future Directions

In this chapter, they take a look at how One Nation, One Law and other complex and controversial socio-legal topics can be better understood with the help of machine learning. By analysing legal texts and public opinion data with AI-driven algorithms, they can learn about the linguistic and doctrinal trends in Indian jurisprudence and the general people's sentiment on the need for legal uniformity. By analysing legal texts and public opinion data with AI-driven algorithms, they can learn about the linguistic and doctrinal trends in Indian jurisprudence and the general people's sentiment on the need for legal uniformity. These findings highlight the fact that people's opinions vary greatly depending on their location, culture, and religion, and they imply that we need to be inclusive and sensitive to the constitution when we adopt policies. With the rise of digital venues for legal and political discourses, machine learning models provide a valuable perspective for scholars, lawmakers, and civil society to comprehend and participate in the unfolding story. To enhance our comprehension of the public and legal processes involved in India's pursuit of legal uniformity, future studies could build upon this framework by integrating cross-linguistic models and longitudinal analysis.

REFERENCES

1. D. Wang and L. Wang, “Deep learning semantic understanding and classification of student online public opinion for new media,” Int. J. Inf. Commun. Technol., vol. 25, no. 10, pp. 62–76, 2024, doi: 10.1504/IJICT.2024.143335.
2. V. Routiya, ONE NATION , ONE SCHOOL : A COMPREHENSIVE ANALYSIS OF THE LEGAL FRAMEWORK IN INDIARoutiya, V. (2024). ONE NATION , ONE SCHOOL : A COMPREHENSIVE ANALYSIS OF THE LEGAL FRAMEWORK IN INDIA. August., no. August. 2024.
3. G. Gupta, “The Debate on ‘One Nation, One Language,’” Int. J. Lang. Law, vol. 11, no. February,
4. pp. 1–17, 2022, doi: 10.14762/jll.2022.001.
5. Dr. Gauri Kala, “Legal Connections Of Concording Personal Laws Through One Nation One Law,” Leg. Connect. Concording Pers. Laws Through One Nation One Law., vol. 9879, no. I, pp. 1–7, 2024.
6. H. Fukurai and R. Krooth, “Original Nation Approaches to Inter-National Law (ONAIL),” in Original Nation Approaches to Inter-National Law, Cham: Springer International Publishing, 2021, pp. 105–179. doi: 10.1007/978-3-030-59273-8_4.
7. T. Gurevich, P. Herman, F. Toubal, and Y. Yotov, “One Nation, One Language? Domestic Language Diversity, Trade and Welfare,” SSRN Electron. J., 2021, doi: 10.2139/ssrn.3774667.
8. A. Chamekh, M. Mahfoudh, and G. Forestier, “Sentiment Analysis Based on Deep Learning in E- Commerce,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 13369 LNAI, 2022, pp. 498–507. doi: 10.1007/978-3-031-10986-7_40.
9. P. Sobkowicz, M. Kaschesky, and G. Bouchard, “Opinion mining in social media: Modeling, simulating, and forecasting political opinions in the web,” Gov. Inf. Q., vol. 29, no. 4, pp. 470–479, Oct. 2019, doi: 10.1016/j.giq.2012.06.005.
10. S. Niu, “Emotion research on education public opinion based on text analysis and deep learning,”
11. Front. Psychol., vol. 13, no. 2017, Oct. 2022, doi: 10.3389/fpsyg.2022.992419.

12. M. Müller, M. Schneider, M. Salathé, and E.

Vayena, “Assessing Public Opinion on CRISPR- Cas9: Combining Crowdsourcing and Deep Learning,” J. Med. Internet Res., vol. 22, no. 8, p.
13. e17830, Aug. 2020, doi: 10.2196/17830.
14. W. Shi et al., “Online public opinion during the first epidemic wave of COVID-19 in China based on Weibo data,” Humanit. Soc. Sci. Commun., vol. 9, no. 1, p. 159, May 2022, doi: 10.1057/s41599-022-01181-w.
15. W. Wan and R. Huang, “Deep Learning-Driven Public Opinion Analysis on the Weibo Topic about AI Art,” Appl. Sci., vol. 14, no. 9, p. 3674, Apr. 2024, doi: 10.3390/app14093674.
16. H. Adamu, S. L. Lutfi, N. H. A. H. Malim, R. Hassan, A. Di Vaio, and A. S. A. Mohamed, “Framing Twitter Public Sentiment on Nigerian Government COVID-19 Palliatives Distribution Using Machine Learning,” Sustainability, vol. 13, no. 6, p. 3497, Mar. 2021, doi: 10.3390/su13063497.
17. S. W. H. Kwok, S. K. Vadde, and G. Wang, “Tweet Topics and Sentiments Relating to COVID- 19 Vaccination Among Australian Twitter Users: Machine Learning Analysis,” J. Med. Internet Res., vol. 23, no. 5, p. e26953, May 2021, doi: 10.2196/26953.
18. M. El Barachi, M. AlKhatib, S. Mathew, and F. Oroumchian, “A novel sentiment analysis framework for monitoring the evolving public opinion in real-time: Case study on climate change,” J. Clean. Prod., vol. 312, no. February, p. 127820, Aug. 2021, doi: 10.1016/j.jclepro.2021.127820.
19. S. Zhou, Q. Chen, and X. Wang, “Active deep learning method for semi-supervised sentiment classification,” Neurocomputing, vol. 120, pp. 536–546, 2020, doi: 10.1016/j.neucom.2013.04.017.
20. C. N. Dos Santos and M. Gatti, “Deep convolutional neural networks for sentiment analysis of short texts,” COLING 2014 - 25th Int. Conf. Comput. Linguist. Proc. COLING 2014 Tech. Pap.,
21. pp. 69–78, 2021.
22. P. Hackett and D. Rennie, “Gated Neural Networks for Targeted Sentiment Analysis Meishan,” Gated Neural Networks Target. Sentim. Anal. Meishan, vol. 309, no. 8009, pp. 491–492, Feb. 2022, doi: 10.1016/S0140-6736(77)91987-0.
23. B. Ma, H. Yuan, Y. Wan, Y. Qian, N. Zhang, and Q. Ye, “Public opinion analysis based on probabilistic topic modeling and deep learning,” Pacific Asia Conf. Inf. Syst. PACIS 2016 - Proc., 2016.
24. J. Li, Y. Wang, and J. Wang, “An Analysis of Emotional Tendency Under the Network Public Opinion: Deep Learning,” Informatica, vol. 45, no. 1, pp. 149–156, Mar. 2021, doi: 10.31449/inf.v45i1.3402.
25. D. Kim, C. J. Chung, and K. Eom, “Measuring Online Public Opinion for Decision Making: Application of Deep Learning on Political Context,” Sustain., vol. 14, no. 7, pp. 1–16, 2022, doi: 10.3390/su14074113.
26. R. Desislavov, F. Martínez-Plumed, and J. Hernández-Orallo, “Trends in AI inference energy consumption: Beyond the performance-vs-parameter laws of deep learning,” Sustain. Comput. Informatics Syst., vol. 38, no. February, p. 100857, 2023, doi: 10.1016/j.suscom.2023.100857.
27. S. Engel, J. Pallas, and S. Lambert, “Model United Nations and Deep Learning: Theoretical and Professional Learning,” J. Polit. Sci. Educ., vol. 13, no. 2, pp. 171–184, 2017, doi: 10.1080/15512169.2016.1250644.
28. J. Huang, G. Cook, and Y. Xie, “Do mass media shape public opinion toward china? quantitative evidence on new york times with deep learning,” arXiv, vol. 2012.07575, 2020.
29. B. Abimbola, E. de La Cal Marin, and Q. Tan, “Enhancing Legal Sentiment Analysis: A Convolutional Neural Network–Long Short-Term Memory Document-Level Model,” Mach. Learn. Knowl. Extr., vol. 6, no. 2, pp. 877–897, 2024, doi: 10.3390/make6020041.