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Advanced Insights in Nursing Science: Applying ARIMA-CLSTM for Concept Analysis

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***Abstract* –The phrase "nursing science" extends much beyond the theoretical underpinnings of topics like asepsis and body mechanics. This lecture takes a classical Aristotelian stance in its examination of scientific concepts, natural phenomena, scientific knowledge, and the procedures of inquiry and proof. After that, it will show how the science is useful by applying traditional approaches to nursing. Preprocessing, feature extraction, and model training must proceed without pauses. A part of preparing data is making sure it is normalized and removing stop words. The GLCM is utilized for feature extraction; however, while it provides a large amount of data, it is not optimal for picture feature extraction, image recognition, or classification. It is necessary to extract features before training an ARIMA-CLSTM model. The suggested method outperforms the state-of-the-art algorithms using the current data. A considerable improvement was noted in terms of accuracy, with the findings reaching 97.33%.**

Keywords—Nurse Education, Evidence-Based Practice (EBP), Long Short-Term Memory (LSTM).

I. INTRODUCTION

Registered nurses (RNs) constitute the largest proportion of the healthcare workforce in the United States and more than half of the healthcare workforce globally, as reported by the World Health Organization and the American Association of Colleges of Nursing. Public health, primary care, home health, outpatient centers, schools, academia, healthcare research, hospitals, and long-term care facilities are just a few of the several healthcare settings where nurses are in high demand. As a group, nurses "distinguishes nurses from other healthcare professionals" due to the immense benefit the system offer. Consideration of the social factors, commonly referred to as determinants that impact individuals' health is one of the initial things that nurses learn. The system are vital in helping people from different socioeconomic backgrounds (regardless of gender, race, occupation, or level of education) connect with one another assets and delivering healthcare services to people where the method are at home or at work. Secondly, nurses do more than just make medical diagnoses; the system also treat the whole person, putting their mental, emotional, and physical health first. In a comprehensive healthcare paradigm, nurses play a crucial role in implementing primary, secondary, and tertiary prevention strategies for vulnerable populations that are at a high risk of developing or worsening health problems. Nursing has a crucial role in both the primary and secondary spheres of infectious disease prevention. In every country, whatever of its socioeconomic development, nursing is the frontline, dedicated profession that helps prevent illness and alleviate suffering before and after treatment for any condition. Nurses have always been at the forefront of developing industry standards for patient care and clinical safety. Crisis, war, natural disasters, and infectious illness pandemics like the COVID-19 all make them more effective and valuable. This system's objective is to analyze the roles, responses, and challenges encountered by nurses in the lead-up to, during, and aftermath of pandemics, and to shed light on their successes in this domain in order to set the stage for this investigation within the first five months of the COVID-19 epidemic. Whether it's in the early stages of COVID-19 mitigation or in response to the outbreak, the writers always stress the importance of nursing in promoting interdisciplinary teamwork and attaining best outcomes. The proposed approach move further into the subject by contrasting the nurses' previous relevant experience with their role in managing the numerous infected patients, their personal sacrifices, and the challenges the system encountered during this outbreak. Critical thinking is a complicated and dynamic process that is built upon attitudes and strategic abilities with the aim of accomplishing a given target or goal. Based on a careful review of descriptive and empirical literature addressing conceptual investigation of critical thinking, the proposed approach conducted an analysis of this topic in clinical practice, training, and research from the standpoint of a virtue ethical framework. The proposed approach use the JBI critical appraisal checklist for research and opinion articles as a framework to analyze the principles and practices of critical thinking in nursing, with an emphasis on how it is applied in scientific investigation, classroom education, and clinical practice. The proposed approach explore the role of critical thinking in nursing diagnoses and care decisions, how to instill these abilities in students, and the significance of critical thinking in nursing research. The development of virtues is the only way to get critical thinking abilities, attitudes, and, consequently, nursing care. The nursing profession is built around human relations and care. Nurses understand the condition of health and disease, come up with appropriate solutions, prevent healthcare concerns, and handle difficulties from the start of life to the end by acting responsibly and with mutual trust. Also, in a trusting environment, one person gives care while the other receives it; this asymmetry is what makes nursing unique. Trust is a fragile and easily manipulated concept. Care giving is fraught with risks, and the recipient's innate fragility compounds those risks. Fundamental components of a nurse's role in a care relationship that assist individuals in maintaining their health include assessing the need for nursing care, developing interventions, providing pre- and post-operative care, monitoring and administering medication, and providing emotional support to patients and family members as the system consider decisions that could have a life-or-death impact. Assistance of this nature influences the quality of healthcare.

II. LITERATURE SURVEY

"The Nursing Process" is the standard operating procedure (SOP) that most people now see nurses following when caring for patients. [1] It consists of phases such as assessment, diagnosis, planning, outcomes, implementation, and evaluation. Every part of modern life is powered by technology these days. Artificial super intelligence (ASI) has enabled a leap from low-fidelity machines to high-fidelity technologies, and the nursing profession has adapted accordingly [2]. The exponential growth of technology has caused a sea change in the healthcare sector. Technology has had a profound effect on the nursing industry's organization and structure. Modal shifts in healthcare delivery have been influenced by developments such as electronic health records (EHRs), biomedical and engineering technology (which enables the development of ever more complex health care technologies), robotics, and artificial intelligence, among others. [3] In order to help nurses provide better, more efficient care to their patients, new technology tools have been developed. The nursing practice of today is very different from that of thirty years ago. There will be new challenges for nurses in the future due to technological advancements in areas like robotic-assisted surgery, companion robots for people with special needs (like the elderly, autistic children, or the disabled), [4]automated dispensing robots (that would make nurses' jobs obsolete), and ever-improving artificial intelligence (that would give machines the ability to make important healthcare decisions and coordinate patient care) while on the job. In order to make judgments based on the best available research and patients' particular values and preferences, healthcare practitioners should adhere to evidence-based practice (EBP) guidelines [5]. The major health professional groups have set EBP competency as a standard for the field because the system regard EBP as an essential part of high-quality therapy [6]. Despite nurses' positive attitudes about EBP, the system lack the education and training necessary to put it into practice. While nursing education is the foundation of evidence-based practice (EBP), numerous studies have focused on the quality of EBP instruction for health science undergraduates. Undergraduate nursing curricula have also been strongly urged to effectively incorporate evidence-based practice (EBP) [7]. As the system embark on their journey to become nurses who deliver top-notch care, nursing students would do well to familiarize themselves with evidence-based practice (EBP) from the very beginning of their undergraduate studies. This will give them the head start the system need to effectively integrate EBP into their clinical practice. A dearth of research methodologies that could assess nursing students' EBP abilities is limiting studies in Greek educational institutions [8]. The Evidence from research indicates that the EBP-COQ possesses adequate psychometric properties and is thus a legitimate scale [9]. A recent scoping analysis identified workload, an unsupportive professional culture and environment, a lack of resources, and an absence of authority to change existing practices as the primary barriers to health professionals implementing evidence-based practice (EBP).New religious movements are appearing or other religions are being acknowledged in countries, as the desire for sanctity and religion becomes more apparent in times of risk and uncertainty, according to some scholars [10]. The importance of religious sentiment as a human dimension in the clinical-welfare domain was highlighted in a study conducted in European intensive care units [11]. The impact of religious engagement on health outcomes has been extensively documented in many journals. Some patients and doctors think that prayer can help them get better. Praying increases the likelihood that hospitalized patients will comply with vaccination requirements, improves immune function, slows the progression of rheumatoid arthritis and reduces anxiety, alleviates pain and promotes health, lessens the impact of illness on children and their families [12], and offers hope when medical intervention fails. For spiritual care, there is a mountain of data concerning training and competency in numerous European countries [13]. Enhancing Nurses' and Midwives' Competence in Provide Spiritual Care via Innovative Education and Compassionate Care, or EPICC, is an effort that has standardized spiritual care education and established a set of skills, attitudes, and knowledge [14].Important training resources include virtual platforms, document-access services, instructional equipment, access to practical training, etc., and their impressions of these tools are critical. According to research [15], student satisfaction is defined as a transient feeling that comes from evaluating one's experience with an educational provider. Classroom design, teachers, pedagogy, environment, enrollment, and supplemental services are all aspects that contribute to students' overall satisfaction with their educational experience several places [16]. Some scholars have proposed the idea of student satisfaction as an individual evaluation of learning outcomes and experiences. Students' levels of satisfaction with their education serve as an indicator of their interest in and success in their coursework and as an evaluation metric for learning effectiveness assessments [17]. Countless studies on student satisfaction have been carried out in different countries in recent years [18] to ascertain the efficacy of online higher education. Ensuring the retention of trained nurses was a main priority in order to protect patients. Consequently, it's evident that mental health and preventing nurses' intentions to quit are significant issues in Korea. [19] A strategy to reduce medical errors, turnover intentions, and related costs might benefit from addressing nurse exhaustion and emotional labor as initial targets. Mental, emotional, and physical exhaustion brought on by long-term stress is known as burnout, while emotional labor refers to the work required to control one's emotions in order to fit in with one's professional or organizational image [20]. The idea of emotional labor has now come to light as a component contributing to burnout and desire to quit in the nursing profession. Several studies have linked emotional labor traits, such as emotional repression and emotional dissonance, to burnout [21]. The proposed approach need more empirical research on the topic of "sustainability at work" if the proposed approach want to help this demographic avoid burnout and keep more of their hard-earned money.

III. Proposed System

This method details the findings of a study that set out to better understand the role of clinical nursing staff in the clinical rotations that undergraduate nursing students had planned to participate in. This proposed seeks to listen to the perspectives of first-year undergraduate nursing students in order to comprehend the role of clinical nurses rather than clinical educators, which is different from past studies. Using a narrative approach, researchers sought to understand how students perceived the role of clinical nursing staff in their clinical education.

A. Preprocessing:

1) Normalization:

It constructed a simple module for abbreviation normalization using web resources; no expert supervision was required. Tabers Medical Dictionaryb and Nurselabsc provided the nursing abbreviations that were scraped using the Python application framework Scrapy 2.0. This framework analyzes webpages and extracts structured data. To keep things clear in collection of nursing acronyms, one can have only included terms with a single definition. Module replaced any occurrences of recognized abbreviations with the long-form and tokenized the free-text to single words using the constructed resource. This allowed us to normalize abbreviations. It was also checked the detection results of an existing system against nursing abbreviation resource.

2) Stop Word Removal:

The proposed approach ran two extra preparation operations to make the compressed normalized text easier to understand. The inflected forms of the words were first simplified to "take." The second step was the elimination of common terms, which are also called stop words. The proposed approach used WordNet's morphy functione, which is implemented in TextBlob, to extract the lemma for words that were designated as nouns or verbs. This process reduced the vocabulary amount while simultaneously considering verb tenses and plurality [22]. Natural Language Toolkit (NLTK), a well-known Python package for working with text data, also features a stop word list that it uses to remove common terms. Although Onix is more popular, the context provided by NLTK's stop word list is more helpful.

B. Feature Extraction:

Still, extracting features from images, classifying them, or recognizing them aren't the best uses of the GLCM's enormous data set. The four statistical indicators of energy, correlation, moment of inertia, and entropy were redefined to capture the GLCM's characteristic information.

Energy is a metric that quantifies the correlation between an image's grayscale and texture distributions; its size is directly correlated to the size of the textures. An increase in the value of the moment of inertia makes the picture texture stand out more [23]. The level of correlation between each pixel in an image is one indicator of its quality. The textural complexity of the target image can be measured by its entropy. As the complexity of the texture rises, the entropy value falls, and vice versa.

Here are the equations:

$$Entropy = \sum_{g} \sum_{f} J(g,f)^2 \tag{1}$$

$$Contrast = \sum_{p=0}^{P_{i_1}} p^2 \sum_{g=1}^{p_i} \sum_{f=1}^{p_i} J(g,f) \tag{2}$$

$$p = |g - f|$$

$$Correlation = \frac{\left[\sum_g \sum_f (g,f) J(g,f) - \beta_c \beta_d\right]}{\alpha_c \alpha_d} \tag{3}$$

$$Entropy = \sum_{g=1}^{2p_i} log\big(J(g,f)\big) * J(g,f) \tag{4}$$

As an example, consider the GLCM element $J(g,f)$, where g and f are integers from 0 $to\ m$. This represents the element's value at the coordinates (g,f). M is the level of the grayscale image.By averaging its four directions, the proposed approach may find the final value of the special parameter. Various kinds of CT images' energy, inertia moment, correlation, and entropy parameters were estimated. The proposed approach used eight computed tomography (CT) scans from three separate sets of lung imaging: one containing cancerous lesions, one containing benign lesions, and one containing healthy persons. When the picture's feature parameters were calculated using energy, entropy, correlation, and moment of inertia, the features of different kinds of samples were not clearly visible. Due to the lack of clear distinction between the feature data of the several categories, the picture classification process was thrown off, even if the four parameters may describe the image's texture information. In order to optimize the GLCM and handle these concerns, the following is an expression of the new feature parameters obtained from the vector and modulus of the four feature vectors that are vectorized:

$$Energy = \overrightarrow{E_0} + \overrightarrow{E_{45}} + \overrightarrow{E_{90}} + \overrightarrow{E_{120}} \tag{5}$$

$$Contrast = \overrightarrow{Con_0} + \overrightarrow{Con_{45}} + \overrightarrow{Con_{90}} + \overrightarrow{Con_{120}} \tag{6}$$

$$Correlation = \overrightarrow{Cor_0} + \overrightarrow{Cor_{45}} + \overrightarrow{Cor_{90}} + \overrightarrow{Cor_{120}} \tag{7}$$

$$Entropy = \overrightarrow{En_0} + \overrightarrow{En_{45}} + \overrightarrow{En_{90}} + \overrightarrow{En_{120}} \tag{8}$$

Every one of those types of CT pictures gets optimized GLCM treatment. Following characteristic parameter vector fitting, there is a significant improvement in the information difference of energy value, correlation, moment of inertia, and similarity of distinct categories of CT images. The issue of subtle feature information differences is typically addressed by the improved GLCM parameters that are based on vector fitting.

C. Model Training:

1) ARIMA:

Previous studies have shown that the ARIMA model is more effective when applied to traffic data, as well as other types of fixed and random time series data. Proposed model takes advantage of ARIMA's pattern-detection capabilities by incorporating it. Integrating integration, moving average (MA), and autoregression (AR(v)) is one popular time series model (u). These concepts are commonly used in statistical models and analyses that aim to forecast time series data. The parameters (v, Y, u) that make up the ARIMA model are described by the equation that follows. Here, v is the order of the autoregressive model, u is the order of the moving-average model, and Y is the difference order.

$$\left(1-\sum_{g=1}^{v} \emptyset_g R^g\right)(1-R)^Y c_s = \left(1+\sum_{g=1}^{u} \theta_g R^g\right)\delta_s \quad (9)$$

The dependent variable c_s, the lag operator L, the AR parameter $\emptyset_g$, the moving average parameter θ_g, and the error term δ_s are all shown in the following equation, which illustrates the ARMA system. Several methods exist for determining the v and u parameters. The system displayed the basic ARIMA algorithm, which consists of three stages. The first thing that has to be done is to find and choose the correct model type. Using the correct parameter Y now, a stationary time series is produced. Estimating the parameters (u, v) is the second phase, and using diagnostic statistics to evaluate the errors is the third. With the right variables and ordering, the ARIMA model can faithfully depict linear connections in time series data.

2) C-LSTM:

The proposed method uses the Conv-LSTM component to capture the traffic flow's nonlinear spatiotemporal properties. I shows the specifics and layer arrangement of the LSTM and convolutional neural networks, which are the main components of this model. Following its description and specification, the shuffle attention layer takes the output vector (Gs t) from the two separate one-dimensional components of the convolutional neural network. The Long Short-Term Memory (LSTM) network can extract temporal features from traffic flow data since it is composed of several layers. The Conv-LSTM part takes data on traffic flows and inputs it with the traffic network's geographical and temporal information. After the proposed approach extract the spatial characteristics from the traffic data using a one-dimensional convolution technique, the proposed approach use a convolution kernel filter and a sliding filter to generate a feature map of the preceding layers. To enhance the acquisition of features and temporal correlations in the traffic data, the proposed approach feed the output of the convolutional layers, which measure the spatial correlations, into the LSTM layers. Keep in mind that RNNs have the potential to convert sequential data into useful temporal characteristics. Problems with long-term performance could arise from RNNs' inability to remember past traffic conditions from time series data due to the vanishing gradient problem. Learning long-term correlations is best accomplished via LSTM because of its memory and storage capacity. In addition, the suggested model has a stacked architecture, which comprises the sequential installation of numerous LSTM layers. Model layers are able to capture higher-level traffic-flow aspects because the system take the hidden state of the layer before them as an input. When trying to boost the efficiency of deep neural networks, this method comes highly recommended.

3) SA:

An important concept described here comes from the field of intelligent transportation systems (ITS) and is based on SA with CNN. Using the SA multiple channel features, which improve the high-level properties of CNNs, yielded the most promising results on prediction tasks. The attention mechanism has been effectively used by numerous systems. The system proposed a shuffle attention model to enable cross-channel interaction, which entails learning feature maps and then shuffling them in the channel dimension [24]. It used the shuffle unit to incorporate spatiotemporal attention for faster feature extraction and modified the standard SA module to classify the input feature map into subsets. The next step is to merge all the secondary characteristics and ensure that the system can communicate with one another by employing a 'channel shuffle' technique. Finally, the proposed approach prove the suggested SA's dependability and show its impact. Reason being, SA's entire structure is shown and explained by its two parts.

a) Channel Attention:

All of this channel's layers revolve around how relevant the input data is. To find the channel's focus, the proposed approach need to shrink the input feature map's spatial dimension. $t \in L^{x/2I\times 1\times 1}$ was proposed as a method for obtaining time-related attributes through the application of global average pooling (GAP), scaling, and activation in order to derive channel-specific statistics. Equation (11) displays this focused attention on the final output channel. Reducing C_{n1} along the spatial dimension $A \times E$ is one approach to conveying this. The GAP algorithm takes an average of all the feature maps rather than adding fully linked layers on top of each one. This strategy has this major benefit.

$$T = J_{GAP}(C_{n1}) = \frac{1}{A\times E}\sum_{g=1}^{A}\sum_{f=1}^{E} C_{n1}(g,f) \quad (10)$$

$$C'_{n1} = \omega\big(J_x(t)\big).C_{n1} = \omega(A_1 t + o_1) \quad (11)$$

In $A_1, o_1 \in L^{x/2I\times 1\times 1}$is a member of the set where the learnable parameters A_1 are continually trained by the network. Sigmoid activation function ω and fully connected (FC) are the basic building blocks of neural networks.

b) SA:

It might say that this level of concentration is a step up from regular focus. The proposed approach offer a normalizing layer that groups channels and applies the Group Norm (GN) across C_{n2} to produce space-wise statistics. The next step is to use Fc(·) to improve C_{n2}s representation. The following equation is relevant when discussing spatial attention:

$$C'_{n2} = \omega(A_2.GN(C_{n2}) + o_2) \quad (12)$$

When A_2, where o_2 is an element of $L^{x/2I\times 1\times 1}$, can undergo continuous training within the network.

IV. Result and Discussion

A number of nursing practices have made use of the critical incident technique. Among these, you can find initiatives to better understand the nursing profession, put measures in place to guarantee high-quality care, evaluate and analyze progress, and encourage reflective practice. This system describes how the method was used as a course evaluation tool for a group of nursing students who were studying comprehensive ENB courses. It shed light on the most important issues that these RNs experienced on the job and how the system demonstrated reflective qualities.

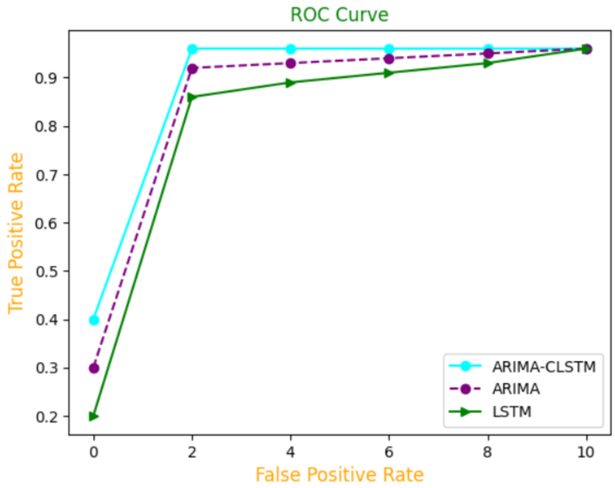

Fig. 1. ROC Curve of the Model

One notable result was ARIMA-CLSTM's AUC-ROC curve score of 0.96. The ARIA-CLSTM model achieved unprecedented success in turnover prediction after adjusting its hyperparameters. The improved ARIMA-CLSTM model attained a 97.33% accuracy in figure 1 when it comes to nursing science insights.

TABLE I. EVALUATION RESULTS(%)

Models	ACC	PRECISION	RECALL	F1
ARIMA-CLSTM	97.33	94.11	96.54	95.78
ARIMA	92.49	89.42	91.25	90.28
LSTM	88.63	85.03	87.62	86.34

Results of experimental investigations into forecasting models table 1 displays the results of the validation and training sets. The results demonstrated that the ARIMA-CLSTM, ARIMA, and LSTM prediction models had the following averages with respect to the training sets: accuracy, F1-measure, precision, and recall. The results demonstrate that when it comes to classification, the ARIMA-CLSTM prediction model outperforms the others. Not only that, ARIMA-CLSTM showed almost perfect prediction performance across all training sets.

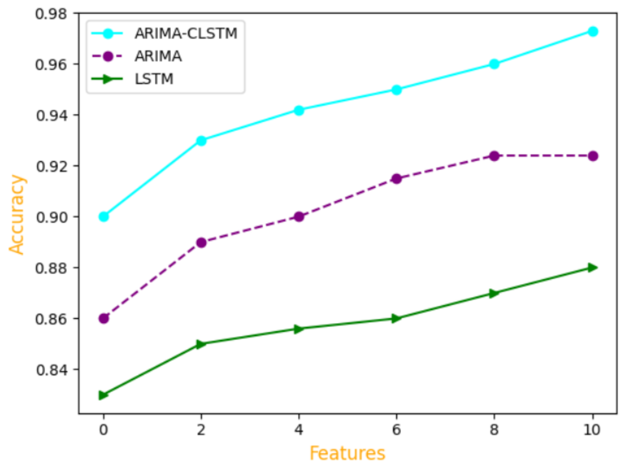

Fig. 2. Comparison of Accuracy

Among the models, Figure 2 demonstrates the one with the best accuracy. The most effective model had two features, and ARIMA-CLSTM was the most accurate. In most cases, accuracy is unrelated to the amount of characteristics.

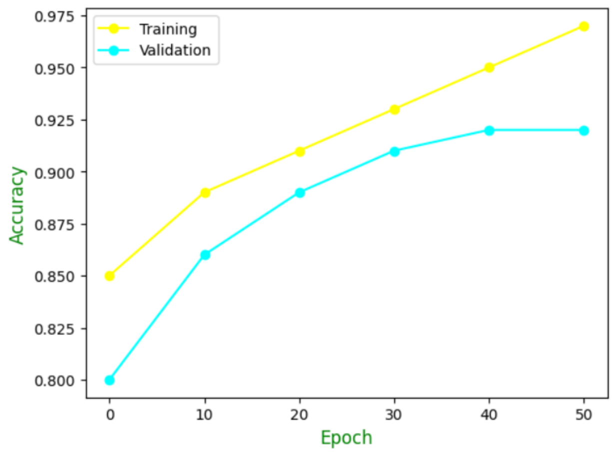

Fig. 3. : Performance Analysis Graph for Accuracy with Epochs

Figure 3 shows the results of the performance analysis of the 3-fold validation set in terms of the accuracy of the training data and the validation data across 60 epochs.

V. CONCLUSION

No amount of rhetorical flourishes can justify ignoring or disrespecting human expressions, particularly metaphor. Attending to metaphorical expressions as an intrinsic whole-in-motion link is an essential part of living one's ideals and decisions in harmony with the art of human development. Many communities depend on healthcare services, and the human-becoming paradigm helps develop confidence by taking a patient-centered approach. Normalizing data and eliminating stop words are aspects of data preparation. Feature extraction is where the GLCM shines; nevertheless, despite its massive data output, it falls short when it comes to picture feature extraction, image identification, and classification. In order to train the model, the ARIMA-CLSTM algorithm makes use of every parameter. With an average accuracy of 96.73%, the proposed technique surpasses both ARIMA and LSTM models.

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