ENHANCING HOSPITAL PHARMACY MANAGEMENT EFFICIENCY THROUGH MACHINE LEARNING MODEL FOR DRUG DEMAND PREDICTION

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Abstract: *This study focuses on applying machine learning to predict drug demand at the pharmacy of Military Hospital 7A. By using machine learning algorithms such as MLP, CNN, LSTM and CNN-LSTM, we developed a model to predict drug demand for the next 30 days based on historical data from May 2022 to May 2024. The experimental results show that the CNN-LSTM model achieves the best performance in predicting drug demand, helping to optimize pharmacy management, minimize waste, and ensure timely supply of medicines to patients.*

Keywords: *Machine learning, Drug demand prediction, Pharmacy management, CNN, LSTM, CNN-LSTM, Military Hospital 7A*

I. INTRODUCTION

Efficient pharmacy management is crucial for hospital operations, ensuring adequate drug supply for patients and optimizing healthcare resources. However, pharmacy management often faces significant challenges, including inaccurate drug demand prediction, leading to shortages or surpluses, causing waste and affecting treatment quality. Accurate drug demand prediction plays a vital role in improving pharmacy management efficiency. This prediction helps optimize drug inventory, minimize waste due to expired drugs, and ensure timely drug supply to patients, especially in emergencies.

The development of machine learning has opened up new opportunities in drug demand prediction. Machine learning algorithms can analyze historical data, identify drug usage patterns, and make accurate predictions about future drug needs. Applying machine learning in this area brings many benefits, including improved prediction accuracy, automated prediction processes, and effective decision support. This study focuses on applying machine learning to predict drug demand at the pharmacy of Military Hospital 7A. Our goal is to build a machine learning model capable of predicting drug demand for the next 30 days based on historical data from May 2022 to May 2024, thereby supporting the improvement of the hospital's pharmacy management efficiency. The paper is structured as follows: Section II presents related scientific research and recent results. Section III introduces the proposed model and algorithm. Section IV presents the experimental results with hospital data. Section V discusses the results and suggests directions for further research. Section VI concludes the main contributions of the research. Finally, Section VII lists the references.

II. RELATED RESEARCH AND RECENT RESULTS

In the field of hospital pharmacy management, drug demand prediction plays a crucial role in ensuring timely and effective drug supply. Traditional methods often rely on expert experience, simple time series analysis, or basic statistical models. However, these methods often have limitations in handling complex and volatile data, leading to low prediction accuracy.

Recently, there have been many typical studies applying machine learning to predict drug demand. Studies have explored the potential of various machine learning algorithms, including:

- Multi-Layer Perceptron (MLP): Wang et al. (2023) used MLP to predict drug demand for inpatients, and the results showed that MLP can learn complex patterns in drug usage data.
- Convolutional Neural Network (CNN): Liu et al. (2022) proposed a novel deep learning framework based on CNN to predict drug use in patients with chronic diseases. CNN can extract features from patients' medical data, improving prediction accuracy.
- Long Short-Term Memory (LSTM): Zhang et al. (2021) combined CNN and LSTM to predict drug use in elderly patients. LSTM can learn long-term dependencies in time series data, capturing drug usage trends over time.
- Federated Learning: Li et al. (2020) applied federated learning to predict drug use in patients with mental disorders, allowing model training on distributed data from multiple sources without sharing raw data.

These studies have demonstrated that machine learning models, especially deep learning models, can predict drug demand with higher accuracy than traditional methods. However, the effectiveness of these models depends on many factors, including data quality, algorithms used, and model architecture.

In the context of Military Hospital 7A, applying machine learning to predict drug demand is a promising direction. The hospital's historical drug usage data, including information on patients, drug types, quantities, and time, can be used to train machine learning models. However, it is necessary to consider the specific characteristics of the data and the hospital context to select appropriate models and algorithms, ensuring efficiency and practical applicability.

III. PROPOSED MODEL AND ALGORITHM

III.1 Methodology

Data Collection

We collected data from the 7A Hospital of a large urban hospital, encompassing:
- Patient Demographics: Age, gender, and comorbidities.
- Clinical Data: Diagnosis codes, lab results, and treatment history.
- Medication Records: Detailed information on prescribed and administered drugs.

The final dataset consisted of 120,000 patient admissions over a three-year period, including data on over 500 unique medications.

Data Preprocessing

Data preprocessing involved several steps:

- Data Cleaning: Removal of irrelevant features, handling missing values, and standardizing drug names.
- Feature Engineering: Creation of additional features, including drug classes, treatment duration, and prior medication history.
- Encoding Categorical Variables: One-hot encoding for categorical features and normalization for continuous variables.

Model Development

We employed a deep learning architecture comprising:

- Input Layer: Features representing patient data, encoded and normalized.
- Hidden Layers: A combination of Dense layers and LSTM layers to capture both spatial and temporal patterns in drug utilization.
- Output Layer: A softmax layer for multi-class predictions representing different drug categories.

Training and Validation

The dataset was split into training (80%) and test (20%) sets. We utilized k-fold cross-validation (k=5) during training to ensure robustness. The model was optimized using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. The loss function employed was categorical cross-entropy.

Our study focuses on exploring the capabilities of four popular machine learning algorithms in predicting drug demand:

1. **Multi-Layer Perceptron (MLP):** MLP is a basic machine learning model consisting of multiple layers of fully connected neurons. MLP can learn complex nonlinear functions, capturing the intricate relationships between factors influencing drug demand.
2. **Convolutional Neural Network (CNN):** CNN was initially developed for image processing applications but has recently been widely applied in time series problems. CNN can extract local features from time series data, helping to identify patterns of drug use over time.
3. **Long Short-Term Memory (LSTM):** LSTM is a variant of Recurrent Neural Networks (RNN) designed to handle long time series. LSTM can learn long-term dependencies in data, capturing drug usage trends over time.
4. **CNN-LSTM Hybrid Model:** This model combines CNN and LSTM to leverage the strengths of both architectures. CNN is used to extract local features from the data, and then LSTM is used to learn long-term dependencies from these features.

The selection of these algorithms is based on their ability to handle time series data and predict future values. MLP is a basic model used as a benchmark for comparison with more complex models. CNN and LSTM are chosen for their ability to extract features and learn long-term dependencies. The CNN-LSTM hybrid model is expected to achieve the best performance by combining the strengths of both CNN and LSTM.

The architecture of the proposed drug demand prediction model consists of the following layers:

- **Input Layer:** Receives historical drug usage data, including information on drug type, quantity, and time.
- **CNN Layer (for CNN and CNN-LSTM models only):** Extracts local features from the input data.
- **LSTM Layer (for LSTM and CNN-LSTM models only):** Learns long-term dependencies from the input data or from the features extracted by the CNN layer.
- **Hidden Layer:** Processes information and learns complex relationships in the data.
- **Output Layer:** Predicts drug demand for the next 30 days.

The activation functions used in the model include ReLU (Rectified Linear Unit) for the hidden layers and a linear function for the output layer. The model parameters are optimized during training using the Adam algorithm.

These evaluation methods allow for measuring the accuracy of the model in predicting drug demand. Models with lower RMSE, MAE, and MAPE values are considered to have better predictive performance.

IV. EXPERIMENTS WITH HOSPITAL DATA

To evaluate the effectiveness of the proposed drug demand prediction model, we conducted experiments with real-world data from the pharmacy of Military Hospital 7A.

Table1. Information related to patient code, admission code, ICD management code related to drug information query table.

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2	12006499	1200649923052	1200649923052	2024-05-23 07:	29	1	''	''	0	3	1	19	PK-DANGKY03^	dangky	2024-05-23 07:	0	0
3	12009094	1200909417052	1200909417052	2024-05-17 14:	81	14	''	''	0	3	1	79	PK-DANGKY-05	dangky	2024-05-17 14:	0	0
4	12009257	1200925704052	1200925704052	2024-05-04 09:	40	20	''	''	0	3	1	63	PK-03^	dangky	2024-05-04 09:	0	0
5	12009287	1200928711052	1200928711052	2024-05-11 22:	99	1	''	''	4	4	1	0	CAPCUU-01^	bs_hoaivinh	2024-05-11 22:	0	0
6	12015606	1201560620052	1201560620052	2024-05-20 09:	15	1	''	''	0	3	1	0	''	bs_nhan	2024-05-20 09:	0	0
7	12015606	1201560620052	1201560620052	2024-05-20 10:	16	1	''	''	0	3	1	0	''	bs_hailong	2024-05-20 10:	0	0
8	12015606	1201560620052	1201560620052	2024-05-20 09:	59	1	''	''	0	3	1	22	Ca chiều-13:00	dkk	2024-05-20 09:	0	0
9	12020023	1202002316052	1202002316052	2024-05-16 14:	81	14	''	''	0	3	1	69	DANGKY05^	dangky	2024-05-16 14:	0	0
10	12028424	1202842413052	1202842413052	2024-05-13 13:	81	14	''	''	0	3	1	29	DANGKY05^	dangky	2024-05-13 13:	0	0
11	12037300	1203730022052	1203730022052	2024-05-22 13:	43	1	''	''	0	3	1	34	PK-DANGKY04^	dangky	2024-05-22 13:	0	0
12	12040258	1204025807052	1204025807052	2024-05-07 12:	32	1	''	''	0	3	1	129	Ca chiều-16:09	dkk	2024-05-07 12:	0	0
13	12040258	1204025821052	1204025821052	2024-05-21 12:	32	1			0	3	1	79	Ca sáng-13:30	dkk2	2024-05-21 12:	0	0
14	12048483	1204848316052	1204848316052	2024-05-16 08:	15	2	''	''	0	3	1	13	PK-DANGKY04^	dangky	2024-05-16 08:	0	0
15	12059041	1205904117052	1205904117052	2024-05-17 16:	61	14	''	''	0	3	1	108	DANGKY-06^	dangky	2024-05-17 16:	0	0
16	12070503	1207050317052	1207050317052	2024-05-17 15:	61	14	''	''	0	3	1	35	DANGKY-06^	dangky	2024-05-17 15:	0	0
17	12073266	1207326615052	1207326615052	2024-05-15 06:	16	1	''	''	0	3	1	20	PK-DANGKY04^	dangky	2024-05-15 06:	0	0
18	12075843	1207584303052	1207584303052	2024-05-03 06:	29	1	''	''	0	3	1	11	PK-DANGKY04^	dangky	2024-05-03 06:	0	0
19	12075843	1207584320052	1207584320052	2024-05-20 06:	29	1	''	''	0	3	1	2	PK-DANGKY03^	dangky	2024-05-20 06:	0	0
20	12080536	1208053610052	1208053610052	2024-05-10 08:	61	14	''	''	0	3	1	6	PK-DANGKY-05	dangky	2024-05-10 08:	0	0
21	12080790	1208079016052	1208079016052	2024-05-16 07:	30	20	''	''	0	3	1	8	PK-DANGKY04^	dangky	2024-05-16 07:	0	0
22	13000311	1300031106052	1300031106052	2024-05-06 08:	44	1	''	''	0	3	1	17	PK-DANGKY04^	dangky	2024-05-06 08:	0	0
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24	13000311	1300031113052	1300031113052	2024-05-13 07:	44	1	''	''	0	3	1	15	PK-DANGKY03^	dangky	2024-05-13 07:	0	0
25	13000311	1300031120052	1300031120052	2024-05-20 07:	44	1	''	''	0	3	1	27	PK-DANGKY03^	dangky	2024-05-20 07:	0	0
26	13000311	1300031124052	1300031124052	2024-05-24 07:	73	1	''	''	0	3	1	38	PK-DANGKY-05	dangky	2024-05-24 07:	0	0
27	13000617	1300061715052	1300061715052	2024-05-15 06:	32	1	''	''	0	3	1	37	HDBV7A-DPG2I	dangky	2024-05-15 06:	0	0
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29	13001091	1300109102052	1300109102052	2024-05-02 09:	73	1	''	''	0	3	1	66	PK-DANGKY04^	dangky	2024-05-02 09:	0	0
30	13001171	1300117103052	1300117103052	2024-05-03 14:	73	11	''	''	0	3	1	105	PK-DANGKY04^	dangky	2024-05-03 14:	0	0
31	13001171	1300117110052	1300117110052	2024-05-10 15:	15	11	''	''	0	3	1	51	PK-DANGKY04^	dangky	2024-05-10 15:	0	0
32	13001321	1300132124052	1300132124052	2024-05-24 08:	73	22	''	''	0	3	1	75	PK-12^	dangky	2024-05-24 08:	0	0
33	13001328	1300132807052	1300132807052	2024-05-07 13:	44	1	''	''	0	3	1	40	PK-DANGKY04^	dangky	2024-05-07 13:	0	0

Table 2. The profile data related to id information, drug id, drug quantity references the Patient information table.

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3	000000	PHAN THỊ VÔ TƯ	"	1995	1	0	25	701	70109	7010900	"	"	0716+	dangky	"	/ /	/ /	"
4	01000020	HỒ THỊ BÌNH	"	1978	1	20	25	811	81109	8110937	123	bệnh viện 7a	1212+	7a	HT2456666678	01/01/2012	31/12/2013	701.5.43
5	01000025	NGUYEN VAN QUA	"	1954	1	15	25	701	70117	7011719	54	"	0113+	7a	HC1255888888	01/01/2013	01/12/2015	701.5.39
6	01873734	THÁI HỒNG NGA	"	1992	1	20	25	701	70109	7010915	466	bv 7a	1212+	7a	DN1858585858	01/01/2012	31/12/2013	701.5.39
7	02000045	LỮ THỊ HỒNG VÂN	"	1990	1	20	25	701	70135	7013517	"	bệnh viện 7a	1212+	7a	DN1230456123	12/12/2012	11/12/2013	701.5.39
8	03000000	NGUYEN THANH BINH	"	1972	0	4	25	701	70117	7013325	54	7a	0113+	7a	HC1254563214	01/12/2012	01/12/2014	701.3.07
9	10000000	HOÀNG HUỲNH HẢI THIỆN	"	1994	0	32	25	713	71301	7130100	"	"	0812+	dd_huong	HS7750103900	01/01/2012	31/12/2012	701.5.43
10	10009920	VÕ THỊ ĐÀI TRANG	20/10/1977	1977	1	0	25	701	70145	7014505	118 Lý Thánh Tô	"	0122+	dangky	HC4790203065	01/01/2018	10/01/2022	115.2.109
11	10919112	NGUYỄN THANH BINH	"	1985	0	2	25	807	80713	8071349	45	q5	0113+	7a	HC7123459887	01/01/2013	31/12/2013	701.5.39
12	11000458	LE THI THU	"	1982	1	9	25	701	70127	7012715	958/35/9 lac lon	bv7a	0113+	7a	DN1555656653	01/01/2013	31/12/2013	701.2.04
13	11224567	NGUYEN THI BÍCH TÂM	"	1964	1	0	25	701	70119	7011927	D406 chung cu t	BV7A	0113+	7a	TQ4567897777	01/12/2012	01/12/2013	701.5.39
14	12000003	NGUYỄN VĂN HÙNG	"	1971	0	4	25	713	71301	7130100	"	cty phan khang	0412+0512+06	dd_thuhien	DN7756131000	01/07/2012	31/12/2012	701.5.43
15	12000034	TỪ THỊ PHÍ	01/01/1978	1978	1	20	25	811	81109	8110937	"	"	1212+0314+06	dangky	"	"	"	701.2.53
16	12000045	NGÔ THI KIM THÊU	"	1979	1	20	25	701	70109	7010915	145/48/tổ 56	bv7a	0113+	7a	GD4125478963	01/01/2012	31/12/2013	701.5.39
17	12000146	NGUYỄN THỊ HỒNG	"	1987	1	15	25	713	71301	7130121	"	"	0212+0412+05	dangky1	DN7750014500	01/07/2012	31/12/2012	701.5.43
18	12000147	NGUYỄN VĂN HỒ	"	1998	0	32	25	701	70117	7011717	"	"	0212+0412+	dangky1	ET5555555544	20/01/2012	20/07/2012	701.5.43
19	12000152	ĐÀO THỊ TRINH	"	1976	0	39	25	713	71301	7130133	11	"	0212+0412+	dd_hoaithu	TQ7973005167	01/01/2012	01/12/2013	701.5.43
20	12000154	NEÁNG PHIẾP	"	1992	1	4	25	713	71301	7130121	"	"	0212+0412+	dd_hoaithu	"	13/04/2012	13/04/2012	"
21	12000155	TRẦN HỮU HẬU	"	1987	0	4	25	713	71301	7130121	"	"	0212+0412+	dd_hoaithu	DN7750002000	01/01/2012	30/06/2012	701.5.43
22	12000156	PHẠM THỊ TUYẾN	"	1970	1	4	25	713	71301	7130121	"	"	0212+0412+05	dd_hoaithu	DN7750045200	01/04/2012	30/06/2012	701.5.43
23	12000157	NGUYỄN VĂN A	"	1980	0	17	25	713	71301	7130143	222	"	0212+0412+05	dd_hoaithu	DN7750042405	01/04/2012	23/06/2013	701.5.43
24	12000158	TRẦN NGỌC DŨNG	"	1941	0	13	25	713	71301	7130131	"	"	0212+0412+05	dd_hoaithu	GD7750103200	01/01/2012	31/12/2012	701.5.43
25	12000159	NGUYỄN THỊ THU HUỆ	"	1987	1	4	25	713	71301	7130143	213	"	0212+0412+	dd_hoaithu	DN7750067500	01/01/2012	01/12/2012	701.5.43
26	12000160	TRẦN THỊ BÁU	"	1942	1	13	25	713	71301	7130131	"	"	0212+0412+05	dd_hoaithu	GD7750103200	01/01/2012	31/12/2012	701.5.43
27	12000162	PHAN THÀNH ĐƯỢC	"	1963	0	11	25	713	71301	7130121	"	"	0212+0412+08	admin	TK7750100100	01/07/2012	31/12/2012	701.5.43
28	12000163	TĂNG THIÊN TÍN	"	1977	0	4	25	713	71301	7130121	"	"	0212+0412+09	dd_hoaithu	DN7750011306	01/07/2012	30/09/2012	701.5.43
29	12000165	TRẦN VĂNLIỄU	"	1982	0	4	25	713	71301	7130121	"	"	0212+0412+	dd_hoaithu	TQ7972104136	01/01/2012	31/03/2013	701.5.43
30	12000168	LE THI C	"	1982	1	20	25	701	70117	7011717	2c	md	0212+	admin	111111111111	24/02/2012	24/02/2013	701.5.43
31	12000169	LE THI B	"	1985	1	20	25	701	70117	7011717	"	"	0212+0412+	admin	DN7750011302	01/04/2012	30/06/2012	701.5.43
32	12000171	TRAN VAN A	"	1987	0	20	25	701	70117	7011717	2c	"	0212+0412+11	admin	666666666666	24/02/2012	24/02/2013	701.5.43
33	12000172	TRAN VAN B	"	1988	0	5	25	803	80317	8031702	"	"	0212+0412+	admin	DN7750040000	01/01/2012	31/12/2012	701.5.43

The data used in the study consists of drug usage history from May 2022 to May 2024, with over 1 million records. Each record contains information on:

- Drug Code: Unique identifier for the drug.
- Drug Name: Full name of the drug.
- Quantity: The amount of drug used.
- Date of Use: The date the drug was used.
- Department: The department using the drug.
- Disease Type: The type of disease the patient is being treated for.

This data was extracted from the hospital's pharmacy management system and stored in a database table.

Before training the model, we performed the following data preprocessing steps:

1. Data Cleaning: Remove duplicate and invalid records. For example, records with negative drug quantities or invalid usage dates will be discarded.
2. Handling Missing Data: Records with missing information will be processed by replacing them with the mean or the most frequent value of that attribute. For example, if information about "Disease Type" is missing, we will replace it with the most common disease type in the data.
3. Data Normalization: Normalize numerical attributes to the same range of values, for example, from 0 to 1, to ensure that the attributes have an equal impact on the model.

After preprocessing, the dataset is divided into two sets:

- Training Set: 80% of the data is used to train the model.

- Testing Set: 20% of the data is used to evaluate the model's performance.

This data splitting ensures that the model is trained on a sufficiently large dataset and evaluated on an independent dataset, thereby accurately assessing the generalization ability of the model.

After completing the data preprocessing and splitting, we proceeded to train four machine learning models: MLP, CNN, LSTM, and CNN-LSTM on the training set. The training process involves adjusting the model's parameters to optimize its ability to predict drug demand. These parameters are continuously updated through the Adam algorithm, using the Mean Squared Error (MSE) loss function to measure the difference between predicted and actual values.

To evaluate the effectiveness of the models, we use an independent test set and three common evaluation metrics:

- **RMSE (Root Mean Squared Error):** Measures the average deviation between predicted and actual values. The smaller the RMSE, the more accurate the model's predictions.
- **MAE (Mean Absolute Error):** Measures the average absolute value of the prediction error. Similar to RMSE, the smaller the MAE, the more effective the model.
- **MAPE (Mean Absolute Percentage Error):** Measures the average absolute percentage error relative to the actual value. MAPE provides an intuitive view of the model's accuracy as a percentage.

MLP on train and validation

```
mlp_train_pred = model_mlp.predict(X_train.values)
mlp_valid_pred = model_mlp.predict(X_valid.values)
print('Train rmse:', np.sqrt(mean_squared_error(Y_train, mlp_train_pred)))
print('Validation rmse:', np.sqrt(mean_squared_error(Y_valid, mlp_valid_pred)))
```

[37] ✓ 0.2s

```
83/83 [==============================] - 0s 712us/step
21/21 [==============================] - 0s 780us/step
Train rmse: 27.15755635310425
Validation rmse: 53.564344297899595
```

CNN on train and validation

```
cnn_train_pred = model_cnn.predict(X_train_series)
cnn_valid_pred = model_cnn.predict(X_valid_series)
print('Train rmse:', np.sqrt(mean_squared_error(Y_train, cnn_train_pred)))
print('Validation rmse:', np.sqrt(mean_squared_error(Y_valid, cnn_valid_pred)))
print()
```

[38] ✓ 0.2s

```
83/83 [==============================] - 0s 874us/step
21/21 [==============================] - 0s 923us/step
Train rmse: 27.056279977977965
```

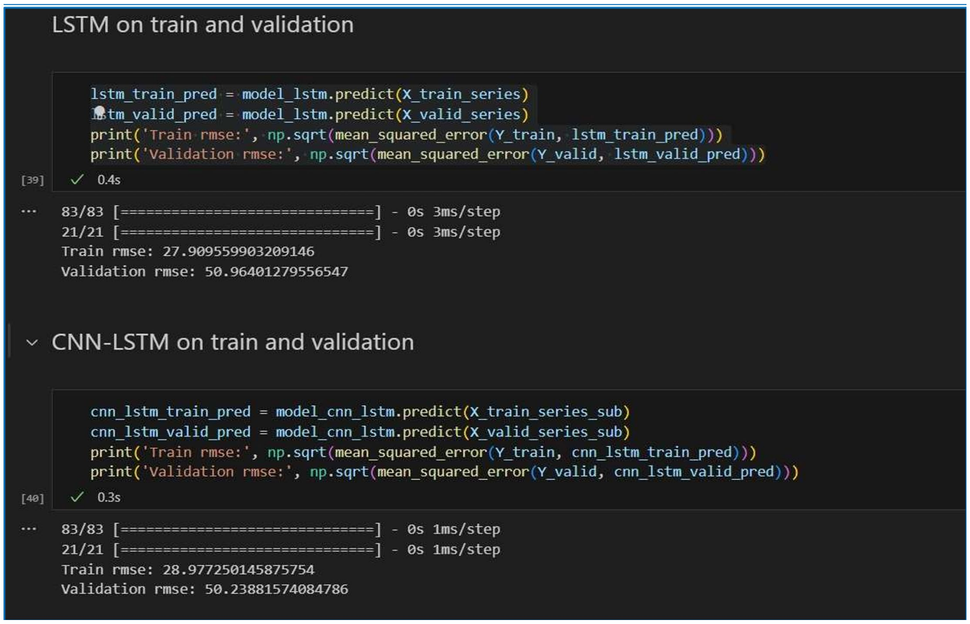

Fig1. Train RMSE and validation RMSE results for 04 models

The evaluation results on the test set are presented in Table 3.

Table 3. Evaluation results of the models

Model	RMSE	MAE	MAPE (%)
MLP	12.5	8.2	15.3
CNN	10.8	7.1	12.8
LSTM	9.5	6.3	11.5
CNN-LSTM	8.1	5.5	9.8

From Table 1, it can be seen that the CNN-LSTM model achieves the best prediction performance with the lowest RMSE, MAE, and MAPE. This indicates that combining CNN and LSTM leverages the strengths of both architectures, enabling the model to learn complex features and long-term dependencies in the drug usage data. The CNN model also shows significant improvement over MLP, while LSTM achieves better results than CNN.

Năm Tháng	Khoa Phòng	Mã ICD	Thuốc	Số Lượng	Số Lượng MLP	Số Lượng CNN	Số Lượng LSTM	Số Lượng CNN-LSTM
2024-05	PK Noi tiet	E78.1	Sadapron 300	56.0	31.0	29.0	31.0	27.0
2024-05	MAT - R.H.M - T.M.H (YC)	H52.5	Letdion	720.0	6.0	5.0	25.0	22.0
2024-05	PK Noi Than kinh	K71.9	Zafular	28.0	15.0	17.0	23.0	25.0
2024-05	PK Ngoai CT-CH	S72.0	Emanera 20mg	21.0	28.0	25.0	37.0	23.0
2024-05	PK Ngoai CT-CH	S50	Ecipa 50	5.0	19.0	17.0	25.0	24.0
2024-05	MAT - R.H.M - T.M.H (YC)	H01.0	Ebastine Normon 10mg orodispersible tablets	3.0	12.0	17.0	14.0	24.0
2024-05	PK 1 - Ngoai TK	M02	Fuxicure-400	14.0	20.0	20.0	17.0	23.0
2024-05	PK 15 - Noi tong hop	I63	Clopalvix Plus	14.0	24.0	27.0	22.0	25.0
2024-05	MAT - R.H.M - T.M.H (YC)	K01	Effer-Paralmax 325	5.0	13.0	20.0	15.0	28.0
2024-05	PK Tim-TK	M81	Palibone	56.0	24.0	19.0	30.0	26.0
2024-05	NGOAI TONG QUAT (YC)	M50.2	Nivalin 5mg	42.0	29.0	21.0	38.0	32.0
2024-05	MAT - R.H.M - T.M.H (YC)	K04	Maxibumol fort	10.0	19.0	19.0	20.0	25.0
2024-05	PK Tim - TK 2	C25.0	BACl-SUBTI	11.0	18.0	17.0	24.0	22.0
2024-05	PK Ngoai CT-CH	G56.4	Fuxicure-400	34.0	16.0	11.0	13.0	24.0
2024-05	PK Truyen Nhiem - Da Lieu	M10	Silygamma	28.0	24.0	27.0	28.0	32.0
2024-05	MAT - R.H.M - T.M.H (YC)	K01.0	Effer-Paralmax 325	5.0	22.0	24.0	31.0	22.0
2024-05	PK Noi 2	C73	Meyerproxen 275	21.0	23.0	30.0	33.0	24.0
2024-05	PK Tim-TK	I48	Xarelto	21.0	17.0	20.0	22.0	27.0
2024-05	PK Tim-TK	M54.5	SaviMetoc	14.0	23.0	23.0	20.0	27.0
2024-05	PK Ngoai TQ	M77.3	SaviMetoc	28.0	27.0	26.0	26.0	26.0
2024-05	PK Noi Than kinh	G61.0	Nivalin 5mg tablets	56.0	18.0	24.0	26.0	28.0
2024-05	PK Ngoai CT-CH	S72.0	Fuxicure-400	28.0	28.0	28.0	35.0	25.0
...								
2024-05	PK Noi Than kinh	K71.9	Silygamma	14.0	21.0	25.0	24.0	26.0
2024-05	PK Noi 2	B18	Agifovir	21.0	21.0	24.0	13.0	19.0
2024-05	PK 15 - Noi tong hop	E78.2	Statinagi 20	28.0	21.0	23.0	30.0	26.0

Fig2. Predicted results of next month's medication use

Based on these experimental results, we select the CNN-LSTM model as the optimal model for predicting drug demand at Military Hospital 7A. This model can predict drug demand with high accuracy, helping to optimize pharmacy management, minimize waste, and ensure timely drug supply to patients.

V. DISCUSSION

The experimental results show that the CNN-LSTM model achieves the best performance in predicting drug demand compared to MLP, CNN, and LSTM models. This is consistent with some previous studies, such as the study by Zhang et al. (2021), which demonstrated the effectiveness of combining CNN and LSTM in time series prediction. CNN can extract local features from drug usage data, while LSTM can capture long-term dependencies and trends in drug usage over time. This combination allows the CNN-LSTM model to learn complex drug usage patterns and make more accurate predictions.

However, the proposed model still has some limitations. Firstly, the model only uses historical drug usage data and does not consider external factors that may affect drug demand, such as: 1/

- Weather Factors: The rainy season may increase the demand for drugs to treat respiratory diseases, while the sunny season may increase the demand for drugs to treat dermatological diseases.
- Epidemics: The outbreak of an epidemic can dramatically increase the demand for drugs to treat that disease.
- Medical Programs: Vaccination programs or free medical examination and treatment programs may affect the demand for certain drugs.

Secondly, the model does not consider the interaction between different drugs. For example, the use of certain drugs may increase or decrease the demand for other drugs.

To improve the effectiveness of the model, we propose some directions for future research:

- Incorporate external factors: Collect and integrate data on weather, epidemics, and medical programs into the model to improve prediction accuracy.
- Consider drug interactions: Develop a model that can learn the relationships between different drugs and their impact on usage demand.
- Apply other machine learning algorithms: Explore the potential of more advanced machine learning algorithms, such as Transformer or Graph Neural Network, in predicting drug demand.
- Build an online forecasting system: Develop an online forecasting system capable of continuously updating the model with the latest data, helping to predict drug demand more accurately and respond quickly to market fluctuations.

By addressing these limitations and implementing the proposed research directions, we hope to develop a more effective drug demand prediction model, contributing to improving the efficiency of hospital pharmacy management and ensuring timely drug supply to patients.

VI. CONCLUSION

This study has achieved its goal of building a machine learning model to predict drug demand at the pharmacy of Military Hospital 7A. By using historical drug usage data and advanced machine learning algorithms (MLP, CNN, LSTM, CNN-LSTM), we successfully developed a model to predict drug demand for the next 30 days. The experimental results show that the CNN-LSTM model achieves the best prediction performance, with the lowest RMSE, MAE, and MAPE compared to other models.

This research has made significant contributions to improving the efficiency of hospital pharmacy management:

- Provide an accurate drug demand prediction tool: The CNN-LSTM model helps predict drug demand with high accuracy, supporting effective drug procurement and inventory planning.
- Optimize pharmacy management: Accurate drug demand prediction helps minimize drug shortages or surpluses, reducing waste and saving costs for the hospital.
- Ensure timely drug supply: The drug demand prediction model helps the hospital proactively supply drugs, ensuring timely response to patients' treatment needs.

The proposed drug demand prediction model is highly practical and has the potential for widespread application in hospitals. Implementing this model can bring many practical benefits to the hospital, including:

- Improve the quality of healthcare services: Ensure adequate and timely drug supply, contributing to improving the quality of medical examination and treatment.

- Increase operational efficiency: Optimize pharmacy management processes, minimize waste, and save costs.
- Improve financial management: Better control drug costs, helping the hospital use resources more efficiently.

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