Interpolating and Forecasting Wound Trajectory using Machine Learning Approaches

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Abstract

Chronic wound treatment and management heavily rely on accurate patient outcome predictions. As chronic wounds become increasingly prevalent in many US states, it's crucial to accurately predict and classify wound progress for timely and effective clinical intervention. The trajectory and outcomes of wounds inform multiple aspects of care, from estimating healing times to understanding disparities in treatment quality and outcomes. For accurate predictions, robust time-series forecast models are required, necessitating comprehensive and consistent wound data. Yet, much of this data is frequently marred by gaps and inaccuracies. In this work, we combined two approaches to overcome this challenge: filling in missing clinical data and forecasting wound healing trajectories. We employed various interpolation techniques, time series, and machine-learning models, including Holt-Winters, ARIMA, Prophet, LSTM, and BiLSTM. Our study assessed 14,571 wounds from 6,171 patients over a five-year span, post-data imputation and interpolation. We introduced a novel approach to firstly impute missing data using XGBoost and then choose the best interpolation method for absent wound data, ensuring precise forecasting without distorting the dataset's demographic makeup. Data for this research was sourced from four wound centers in XX and eight research studies, focusing on a diverse range of wound-related demographics, clinical, and omics data. This comprehensive approach enhances wound trajectory predictions, providing clinicians with valuable insights to formulate personalized treatment plans for both individual patients and demographic groups. This will aid clinicians in better understanding wound healing trends and crafting targeted treatment strategies.

Keywords: Predictive models, Health informatics, Data analysis, Information analysis, Forecasting, Wounds, Health care

1. Introduction

Chronic wounds, failing to heal in a predictable amount of time, represent a significant and growing health concern, especially in developed countries. The prevalence of chronic wounds, including diabetic foot ulcers, venous leg ulcers, and pressure ulcers, is on the rise. A report by Sen et al. (2009) highlighted the increasing threat of chronic wounds, particularly in the United States, where millions are affected with associated medical costs in billions. Accurate determination of a wound's healing trajectory can markedly influence clinical decisions, potentially optimizing treatment outcomes. Frykberg and Banks (2015) highlighted the importance of understanding the underlying pathophysiology and managing factors that contribute to delayed healing to achieve successful healing. With the advancement of computational methods, Machine Learning (ML) models present an avenue with significant promise in refining our predictions regarding wound healing trajectories. For example, Robnik-Sikonja et al. (2003) used ML methods and attribute estimation algorithms to rank prognostic factors and build models for predicting the wound healing rate.

However, the challenge before making a good prediction is that of data quality. As observed by Henry et al. (2013), missing data can be multifactorial, leading to inaccurate and inconsistent predictions. Thus, it's essential to develop techniques to rectify and interpolate these data, ensuring the most reliable foundation for predictive models. In this paper, we combine ML approaches for both predicting wound healing trajectories and refining underlying data through interpolation techniques, aiming to provide clinicians with robust insights for improved wound care.

The investigation of wound progression and outcomes has gained considerable prominence in recent years. Wound care is an interdisciplinary domain that strives to deepen the understanding of wound healing processes, pinpoint elements affecting wound care results, and devise innovative strategies to refine the healing process (Sen (2019)). Many complex processes involved in wound healing rely on the interaction of multiple time-dependent components (Robson (2001)), which may or may not require multivariate forecasting (Paddo et al. (2023)). Precise estimation of wound healing duration will enable clinicians to customize treatment approaches and allocate resources effectively, thus augmenting patient outcomes (Gould et al. (2015)). Factors such as socioeconomic status, geographic location, and health insurance provisions and addressing disparities in care access, can enhance wound care quality and patient satisfaction (Lindsay et al. (2017)). Furthermore, Margolis et al. (2005) showed that disparities in wound care services, such as differences in access, quality, and outcomes, can contribute to health inequalities among diverse population groups. By identifying and addressing these disparities, researchers and practitioners can develop targeted interventions to ameliorate wound care outcomes for susceptible populations (Menke et al. (2007)). Recent work on COVID-19 resource usage shows that demographic details are essential to make disease trajectory predictions (Tariq et al. (2021)). Thus, having complete demographic data is critical for disease trajectory prediction. This article describes a novel ML-based approach to impute missing demographic data and interpolate lost-to-follow-up wound measurement. We provide evaluation results to demonstrate the usefulness of our method that can be used to improve wound trajectory and forecasting.

We developed our work to use the data imported to DHIS2, a popular open-source data warehousing platform, with patient-specific reports that use models to forecast when and how a wound will heal based on wound assessment or visit information. To validate our work, we used data from Net Health Wound Care (formerly WoundExpert) (NetHealth) to train the models with a large number of data values.

2. Related Works

As our initial work revolved around using ML methods to overcome the problem of finding chronic wound trajectory over the period of time a patient visits a care center, we explored the use of ML-based algorithms in overall wound care research. Christie et al. (2019) examined the prediction of patient outcomes following severe injury, revealing accurate predictions using the SuperLearner algorithm. Rittenhouse et al. (2019) utilized the WoundFlow software to map burn wounds and identify factors affecting healing, finding associations with age, burn severity, and renal dysfunction. Liu et al. (2018) focused on predicting open wound size, achieving high accuracy with a combined ML model. Nguyen et al. (2020) investigated machine learning classifiers for wound care decisions, highlighting improved accuracy with clinical expert input. Cukjati et al. (2001) explored wound healing rate prediction using regression trees and a mathematical model. These studies demonstrate the diverse applications of wound trajectory research, including forecasting healing time, improving access to care, addressing disparities, and enhancing outcomes. Effective record management systems play a crucial role in supporting such research endeavors.

Assessment of wound healing may be subjective, where a healed/healing wound can be differentially defined based on the purpose of the research or clinical study (Wallace et al. (2017) & Enoch and Leaper (2008)). Understanding the wound healing trajectory from each patient level data can be used in precision medicine with a consensus that each patient's wound healing trajectory tends to differ. Therefore, we have objectively tried to show each patient's wound healing trajectory and predict their future healing process from the forecasting models.

It has been seen from several studies that predictive models built on ML approach can be effective in predicting medical and omics data such as works by Golas et al. (2018), Alotaibi (2019), Wang et al. (2019) and Nair et al. (2018). The wound healing trajectory result was stratified based on the patients' features, such as gender, race, and ethnicity. As we had many missing information in these features, we applied Missing Value Estimation methods to impute the missing values. Troyanskaya et al. (2003) and Thirukumaran and Sumathi (2012) have discussed about kNNImpute method and different algorithms to improve the efficiency of the imputation, respectively. From a correctly interpolated dataset, getting to know future stratified wound healing trajectory from an ML model, healthcare providers can largely benefit from seeing the trajectory of a wound; alternative patient care or treatment methods can be developed. Thus machine learning approaches could enable visualization of a patient's wound trajectory to help identify wound

Table 1: Baseline Wound Trajectory Models' Performance

	Baseline for REDCap Research Wounds		**Robson et al. (2000)**	**Payne et al. (2011)**
Model	LSTM	Auto-ARIMA	Linear Regression	Linear Regression
# wounds	320	380	83	171
Average R^2	1	0.94	0.98	0.97

care measures that could better benefit the patient in the long run.

Time-series forecasting models, while a powerful tool for predicting future events based on past data, are not immune to the biases that can be inherent in their training data, especially when this data reflects systemic inequalities related to race, ethnicity, or gender. For instance, predictive policing algorithms, which often utilize time-series data to forecast crime rates and deploy resources accordingly, can perpetuate racial biases present in historical arrest data. This leads to a vicious cycle where minority neighborhoods are over-policed, skewing future data and predictions Lum and Isaac (2016). Another example in healthcare is using algorithms to predict future patient needs. Obermeyer et al. (2019) found that an algorithm widely used to guide care decisions was less likely to recommend additional medical assistance for Black patients than for White patients with similar health conditions. This was because the algorithm was trained on cost data, and not actual patient needs, reflecting existing disparities in healthcare spending. Gender bias can also creep in; for instance, when forecasting purchasing behaviors, past data might reflect gendered buying patterns, leading models to pigeonhole consumers into stereotypical categories Datta et al. (2014). It's crucial to be aware of these pitfalls to ensure that time-series forecasting models are both accurate and equitable. Thus, for every model that we built in this project, we performed subgroup analysis by gender and race-ethnicity (see Table 4) before deployment.

Our initial wound trajectory forecasting was done on eight research studies from REDCap, which we consider baseline models. Literature shows that linear regression achieved good results in clean, well-organized data in clinical trials in controlled groups. However, linear regression models (GEE/GLM) did not often perform well on incomplete data. Forecasting performance from baseline and related work is shown in Table 1.

3. Methodology

3.1. Data Collection

To develop ML models and time-series forecasting of wound trajectory, we retrieved data from WoundExpert hosted at XX. The wound data contained 1173 data tables. To navigate through the data and accelerate the data analysis process, we created a data dictionary for the elements in the data tables.

3.2. Building a Framework of Large Wound Registry Data

The study received approval from the Institutional Review Board (IRB) at XX. When analyzing data tables from WoundExpert, it was evident that many did not provide the necessary information for our wound forecasting models. Out of 1,161 tables, a significant number were either null, incomplete, or lacked essential data columns, such as wound/document ID or patient ID.

Furthermore, wound assessments from various clinics demonstrated inconsistencies in the data quality needed to develop a robust forecasting model. Some examples included inconsistent wound assessment data for consecutive dates or varying assessment details on the same date. The data also contained outliers which were subsequently removed. To enhance data quality and address these inconsistencies and outliers, we employed multiple interpolation and forecasting models for all patients in WoundExpert.

3.3. Data Imputation

To stratify our forecasted model performance by categories like gender, race, and ethnicity, we needed to fill in missing information for many patients. We chose the XGBoost Classification, an ML-based method, to estimate these missing values. For training this model, we used data like

Table 2: Gender, Race and Ethnicity Distribution before and after Imputation using XGBoost Classifier

	Before Imputation			After Imputation		
Gender	*Count*	*Percentage*	*Unknown Gender Count*	*Count*	*Percentage*	*Unknown Gender Count*
Male	3833	51.87%	10	3841	51.91%	0
Female	3556	48.13%		3558	48.09%	
Race	*Count*	*Percentage*	*Unknown Race Count*	*Count*	*Percentage*	*Unknown Race Count*
White	3240	83.40%	3514	6277	84.84%	0
Black	588	15.14%		885	11.96%	
Asian	24	0.62%		52	0.70%	
ASKU(Ask but Unknown)	22	0.57%		147	1.99%	
American Indian/ Alaska Native	6	0.15%		9	0.12%	
Native Hawaiian/ Other Pacific Islander	3	0.08%		20	0.27%	
Other	2	0.05%		9	0.12%	
Ethnicity	*Count*	*Percentage*	*Unknown Ethnicity Count*	*Count*	*Percentage*	*Unknown Ethnicity Count*
Non-Hispanic	4930	97.99%	2368	7222	97.61%	0
Hispanic	92	1.83%		168	1.83%	
Patient Declined	8	0.16%		8	0.11%	
ASKU	1	0.02%		1	0.01%	

age, smoking status, BMI, wound measurements, number of wounds, and the existing gender, race, and ethnicity details from a combined data frame. For fine-tuning the model, we made the following adjustments: Maximum depth of each tree: 12; Number of features considered at each split: log base 2 of the total features; Maximum number of leaf nodes: 3 and Total number of decision trees: 25. These settings determine the model's complexity, the way it selects features, and the total trees in the ensemble. Once trained, the model helped us fill in the missing gender, race, and ethnicity details for some patients.

After this process, we compared data distribution before and after imputation. There was a minor difference, so we conducted the Kruskal-Wallis test. The results, with a test statistic of 0.92 and a p-value of 0.34, showed no significant difference in data distribution before and after the imputation. Table 2 shows distribution before and after imputation.

3.4. Data Cleaning

Few patients had only one wound assessment. We excluded these patients because a single assessment doesn't allow for any predictions about the wound's past or future trajectory. Next, we discarded data for patients with multiple wounds when specific wounds only had one assessment. Ultimately, our refined dataset only included wounds with at least two assessments in the WoundExpert database.

During the final step of data interpolation, some wounds, despite having multiple assessments, only had between 2 to 5 total visits. This small number of assessments made validation on a test set challenging. Thus, we categorized these as "Lost to Follow-up" wounds due to their limited visits and removed them from further analysis.

3.5. Interpolation

We used various interpolation methods to fill in the missing data for wound measurements. However, since we've identified three primary patterns in wound area distribution - Radial, Polynomial, and Linear - we have chosen to focus on these three interpolation types. For polynomial types, we have chosen Akima1D and Krogh interpolation methods.

3.6. Methodological Improvement in the Interpolation

Before diving into forecasting, we applied various interpolation methods to our preprocessed data. For our forecasting models, which can be time-series or neural network-based, it's essential to have a comprehensive dataset. This meant that any missing assessment data in the wounds had to be interpolated. We found that relying on just one interpolation technique wasn't effective for many of the wound measurements. Recognizing this, we suggested a more flexible approach to selecting interpolation methods. We noticed that inaccurate interpolation led to poor outcomes when using the time-series models. Some interpolation methods have constraints, like the Akima1D method, which requires at least five data points.

To address this, we tried interpolating using three different types of wound assessment data: Radial, Polynomial, and Linear. We then evaluated the results using the Akaike Information Criterion (AIC) to determine the most suitable method for each wound. Among the Polynomial interpolation methods, we specifically looked at Krogh and Akima1D, given their popularity. For each wound, the interpolation method that yielded the lowest AIC was chosen to complete the missing data. For those interested, the code detailing our data cleaning, merging, interpolation, and forecasting model is available here: `https://anonymous.4open.science/r/wound-forecast-0271/`.

3.7. Time-Series Forecasting Models

We used 5 forecasting models to forecast the future wound healing trajectory - Holt-Winters, ARIMA, Prophet, LSTM, and BiLSTM. Each of the models was suitable for certain types of wounds. Each model was run on the interpolated data of the individual wounds.

3.7.1. Holt-Winters

Holt-Winters is a well-known model to see the time series behavior of data. Through Holt-Winters, we can see three aspects of time-series data which are average, slope or trend, and cyclical repeating pattern or seasonality.

3.7.2. Auto-ARIMA

An Auto-Regressive Integrated Moving Average (ARIMA) model is an advanced way of predicting time-series data (Shumway and Stoffer (2017)).

3.7.3. Prophet

Prophet was first introduced by Facebook and proposed by Taylor and Letham (2018). As Prophet was originally proposed for forecasting daily data with weekly and yearly seasonality and was later extended for seasonal data as well, we opted for it to get the forecasted wound trajectory as well.

3.7.4. LSTM

LSTM, or Long Short-Term Memory, is a special type of Recurrent Neural Network (RNN) and can be enabled to learn long-term dependencies in data. LSTM is used in time-series forecasting because of the spatio-temporal nature of wound data. An LSTM network learns from a sequence of past data as input and presents an output observation. Several researchers have used LSTM networks for forecasting time-series data Zhao et al. (2017), Abbasimehr et al. (2020), Sagheer and Kotb (2019) and Huang et al. (2020).

Table 3: Interpolation Result on The Wounds

		Good Interpolation RMSE<5 MAPE<5		**Bad Interpolation RMSE>5 MAPE>5**		**Total Interpolation**	
Number of wounds		*n=14417*		*n=154*		*n=14571*	
		Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Interpolation Method Validation Metrics	***AIC***	294.07	946.65	3576.05	3722.80	328.76	1069.98
	RMSE	0.45	0.92	44.88	60.49	0.92	7.74
	MAPE	0.20	0.51	300.80	1867.02	3.38	193.80
	R^2	0.84	0.27	0.46	0.32	0.83	0.27
Interpolation Method Distribution	***Linear***	65.35%		82.47%		65.53%	
	Krogh	15.47%		1.30%		15.32%	
	Akima1D	13.41%		5.84%		13.33%	
	RBF	5.77%		10.39%		5.82%	

3.7.5. Bi-LSTM

Bi-LSTM or Bi-Directional Long Short-Term Memory uses two independent LSTM networks together. Thus the network has both backward and forward information from the sequence while training the model. Bi-LSTM has shown promising results in time-series forecasting, particularly in data that has cyclical or multi-directional characteristics Suebsombut et al. (2021), Sunny et al. (2020) and Shahid et al. (2020).

4. RESULTS

4.1. Merged Data Frame & Imputation by XGBoost Classifier

The final merged data frame from six data tables gave us a dataset having 1,726,834 rows and 11 columns. The 1,72,6834 rows represented the number of total wound assessments, and 11 columns represented the features, including Patient Identification Number, corresponding Date of the assessment (Converted from Date-Time format to Date format for simplicity), Wound Number, Length and Width information of the wound on the assessment day, Patient's gender, Race, Ethnicity, Age, BMI, and Smoking Status.

Before imputing gender, race, and ethnicity, there were 3,833 known male patients, 3,556 known female patients, and missing values for 10 patients' gender, 3,514 patients' race, and 2,368 patients' ethnicity. We filled in these missing values using a machine learning-based imputation method (3.3). The results are shown in Table 2.

4.2. Interpolation

After data cleaning, we found 14,918 wounds for which interpolation could be done (having more than one assessment). But some wounds (n=347) were considered Lost to Follow-up wounds as the total number of visit days after interpolating these wounds was much less (2/3/4/5 days); thus, we couldn't validate such data. So we finally analyzed 14,571 wounds. Each interpolation method (RBF, Krogh, Akima1D, Linear) was applied to each wound's data, and the AIC values for each fitted interpolation function were noted. For each wound, we selected the interpolation method with the lowest AIC value as the final interpolation and noted the interpolated values. To verify the technique, we re-interpolated the data for each wound, repeating the method of switching to the best-fitted interpolator again. We kept random 20% sequential data of the interpolated data from the first interpolation for testing and used the remaining data (80% of the total data) to do the re-interpolation. We evaluated the results by calculating RMSE, MAPE, and R^2 values for the removed data (Test set) and interpolated data (Predicted set) from the second interpolation. The average values of the metrics are shown in Table 3.

4.3. Wound Healing Trajectory Prediction through Time-Series Model

We have used the previously mentioned method of interpolation and got the missing visit date and the corresponding wound assessment information for each wound i.e. patient, and used those interpolated information in the models for prediction. Table 4 shows the accuracy measures from the results of the forecasting models. The validation of the model result has been obtained through the accuracy metrics as RMSE and R^2 value. The interpolated values and original along the predicted trajectories by two best performing models (Prophet and BiLSTM) for one random wound are shown in Fig. 1.

5. DISCUSSION

The trajectory of wound healing is a complex process influenced by a myriad of factors. To adequately capture the nuances and variability of this process, it is imperative to consider subgroup analyses in forecasting models.

Biological Variability: Wound healing rates can differ significantly based on individual factors such as age, gender, and genetic background (Gurtner et al. (2008)). A model that doesn't differentiate between these subgroups might overlook critical nuances, potentially leading to inaccurate or overly generalized predictions.

Ethnic and Racial Differences: Ethnic and racial differences can play a significant role in wound healing trajectories. For instance, certain populations may be more susceptible to keloid and hypertrophic scars (Bayat et al. (2003)). By not accounting for these differences, forecasting models risk missing important population-specific trends, which could be essential for tailored interventions.

Subgroup analyses provides a more granulated view, ensuring that predictions are both accurate

Table 4: STRATIFIED AVERAGE ACCURACY METRICS FOR THE FORECASTING MODELS

Models			**Holt-Winters**	**AutoARIMA**	**Prophet**	**LSTM**	**BiLSTM**
Features for Stratified Result		**Accuracy Metrics**	***Average (±SD)***	***Average (±SD)***	***Average (±SD)***	***Average (±SD)***	***Average (±SD)***
Gender	*Female*	*RMSE*	14.71 (±75.04)	4.84 (±48.64)	**2.58 (±15.20)**	4.84 (±24.85)	6.04 (±28.30)
		R^2	0.78 (±0.30)	0.86 (±0.25)	0.84 (±0.27)	0.86 (±0.18)	**0.93 (±0.17)**
	Male	*RMSE*	20.14 (±151.83)	6.17 (±88.88)	**3.07 (±18.05)**	6.17 (±22.74)	6.75 (±33.31)
		R^2	0.76 (±0.31)	0.86 (±0.25)	0.83 (±0.28)	0.86 (±0.17)	**0.92 (±0.17)**
Race	*White*	*RMSE*	17.80 (±122.13)	6.21 (±79.06)	**2.91 (±17.26)**	6.21 (±23.79)	6.47 (±31.78)
		R^2	0.77 (±0.30)	0.86 (±0.25)	0.84 (±0.27)	0.86 (±0.17)	**0.93 (±0.17)**
	Black	*RMSE*	17.67 (±139.49)	**1.50 (±10.84)**	2.60 (±14.75)	1.50 (±24.59)	6.38 (±28.71)
		R^2	0.73 (±0.32)	0.86 (±0.25)	0.81 (±0.28)	0.86 (±0.20)	**0.91 (±0.18)**
	Asian	*RMSE*	2.37 (±0.82)	1.13 (±6.29)	**0.48 (±0.93)**	1.13 (±1.18)	1.25 (±3.17)
		R^2	3.73 (±0.26)	0.81 (±0.31)	0.78 (±0.32)	0.81 (±0.14)	**0.94 (±0.15)**
	ASKU	*RMSE*	16.84 (±65.53)	**1.24 (±6.20)**	2.47 (±8.11)	1.24 (±16.51)	6.11 (±14.07)
		R^2	0.78 (±0.29)	0.90 (±0.22)	0.79 (±0.31)	0.90 (±0.13)	**0.91 (±0.21)**
	Native Hawaiian or Other Pacific Islander	*RMSE*	19.93 (±20.01)	**1.44 (±1.39)**	1.66 (±1.95)	1.44 (±9.41)	7.36 (±6.31)
		R^2	0.80 (±0.23)	0.93 (±0.07)	0.64 (±0.42)	0.93 (±0.15)	**0.93 (±0.09)**
	American Indian or Alaska Native	*RMSE*	28.82 (±41.73)	4.35 (±6.87)	**1.53 (±1.43)**	4.35 (±14.08)	10.14 (±20.41)
		R^2	**0.96 (±0.06)**	0.77 (±0.36)	0.85 (±0.22)	0.77 (±0.09)	0.95 (±0.11)
	Other	*RMSE*	0.44 (±0.39)	**0.02 (±0.01)**	0.03 (±0.04)	0.02 (±0.23)	0.08 (±0.06)
		R^2	0.95 (±0.07)	0.78 (±0.37)	0.64 (±0.55)	0.78 (±0.40)	**1.00 (±0.00)**
Ethnicity	*Non-Hispanic*	*RMSE*	17.83 (±124.12)	5.63 (±74.20)	**2.87 (±16.94)**	5.63 (±23.86)	6.47 (±31.35)
		R^2	0.76 (±0.31)	0.86 (±0.25)	0.83 (±0.28)	0.86 (±0.17)	**0.92 (±0.17)**
	Hispanic	*RMSE*	8.32 (±18.12)	**1.42 (±7.69)**	1.43 (±4.33)	1.42 (±9.29)	3.82 (±9.56)
		R^2	0.78 (±0.29)	0.87 (±0.25)	0.83 (±0.28)	0.87 (±0.18)	**0.92 (±0.19)**
	Patient Declined	*RMSE*	1.36 (±2.08)	0.46 (±0.90)	**0.39 (±0.39)**	0.46 (±1.26)	0.94 (±1.35)
		R^2	0.94 (±0.08)	0.78 (±0.31)	0.76 (±0.31)	0.78 (±0.20)	**0.95 (±0.17)**

and relevant to specific populations. This tailored approach not only enhances the validity of the models but also offers actionable insights for clinicians seeking to optimize patient care.

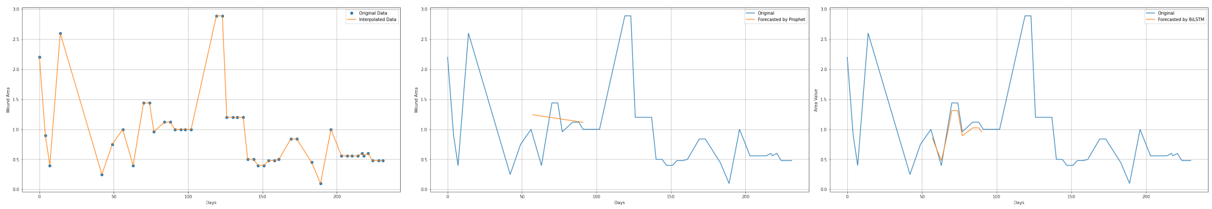
Interpolation Challenges and Solutions: During our interpolation process, we faced issues with some wounds resulting in high mean absolute percentage error (MAPE) values. The root of this problem was a zero divide error when calculating MAPE due to some interpolated wound area values being zero. To rectify this, we added a small value (1e-3 sq cm.) before interpolation, but only where necessary. Fortunately, these cases were minimal. Remarkably, imputing features like gender, race, and ethnicity yielded values that aligned statistically with their original distribution. Our interpolation was successful for 98.94% of the wounds, but for the remaining 1.06%, alternative interpolation methods might be required.

Modeling and Insights: We explored five different models for each wound's interpolated data: Holt-Winters, Auto-ARIMA, Prophet, LSTM, and BiLSTM. The LSTM model demonstrated superior wound healing trajectory predictions. However, a subset of wounds, with minimal visit dates, posed challenges for the AutoARIMA, LSTM, and BiLSTM models. Specifically, patients with only two recorded visits, spaced a single day apart, yielded just three days of interpolated visit data, insufficient for time-series training. It emphasizes the importance of regular patient visits and meticulous data documentation for accurate forecasting.

Considerations with Wound Visit Data: Wound measurements are typically documented weekly during clinic visits, while other clinical data may be inconsistent. Due to this, we chose to focus on reliable, weekly wound measurement data for a univariate forecasting approach over a multivariate one. While literature highlights the importance of demographics in forecasting, our models, stratified by demographics, displayed minimal biases across subgroups, suggesting consistent care strategies. However, to decisively ascertain model biases, further in-depth analysis and exploration of other models are recommended.

5.1. Future Work

A primary goal of our study is to harness our time-series model to predict wound healing trajectories, benefiting healthcare providers and researchers. We aim to automate the entire data analysis and modeling process using the DHIS2 instance we've set up.



(*a*) Interpolation (*b*) Prophet (*c*) BiLSTM

Figure 1: (a) Interpolated values (Orange Line) and Original values (Blue Circles)
(b) Original (Blue) and Predicted-Test (Orange) Wound Healing Trajectory by Two Best Performing Time Series Forecasting Models for One Random Wound

Further enhancements to the forecasting models are also on our horizon. We're considering a multimodal approach incorporating tabular data from WoundExpert and weekly wound images.

While we've focused on univariate forecasting in this study, multivariate forecasting—integrating demographics with visit information—represents an exciting avenue for future exploration. We initially opted for univariate models for simplicity and computational efficiency. But, expanding into multivariate modeling might offer deeper insights into wound healing trajectories.

6. CONCLUSIONS

Our study introduced an ML approach to improve wound trajectory forecasting by addressing missing demographics and incomplete wound assessment records. Our approach fills in gaps in patient information, enabling healthcare professionals to fill in missing data, gain insights into healing trends, and develop personalized treatment plans. Results show improvement while highlighting the importance of efficient record management systems for wound care research.

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