INFO-B 585 BIOMEDICAL ANALYTICS

BIOMEDICAL ANALYSIS ON SIERRA LEONE USING DHIS2

PRANAVI SHAKKARI
(Group 4)

1. Introduction:

Sierra Leone is a country in Africa located on the southwest coast of the continent. The people of the country suffer from poor health and poor infrastructure. Medicare is difficult to access for the general public. The country witnessed many epidemic outbreaks like yellow fever (World Health Organization., 2003) and malaria (Centers for Disease Control and Prevention, 2017). The country also had a poor record of high maternal mortality rate (UNICE, 2019) and infant mortality rate (Central Intelligence Agency, n.d.).

This project performs various analyses of Sierra Leone's health data to understand, share findings, and predict future trends.

2. Data and Tools:

The data is present in the DHIS2 platform. The platform is equipped with visualization features to perform analysis. The platform also enables exporting data into CSV, XLS, and many other formats to study the data more deeply in other platforms which are not supported in DHIS2 now. In such scenarios, R is the preferred language to perform the analysis.

3. ANC IPT Coverage:

Malaria during pregnancy has severe health consequences for pregnant women and developing fetuses (Odjidja et al., 2017). According to research, malaria during pregnancy can cause severe maternal anemia, cerebral malaria in women, and low neonatal birth weight, which can lead to preterm delivery and death (Odjidja et al., 2017).

The ANC IPT Coverage denotes the anti-malarial vaccination given to pregnant women. In this analysis, we consider ANC IPT 1 Coverage and ANC IPT 2 Coverage of Sierra Leone for the last 12 months (i.e., December 2021 to November 2022).

We used a grouped bar plot to denote the monthly vaccination coverage. We could also use comparative line charts or scatter plots to plot the monthly vaccination coverage. The grouped bar plot showed better visual appeal.

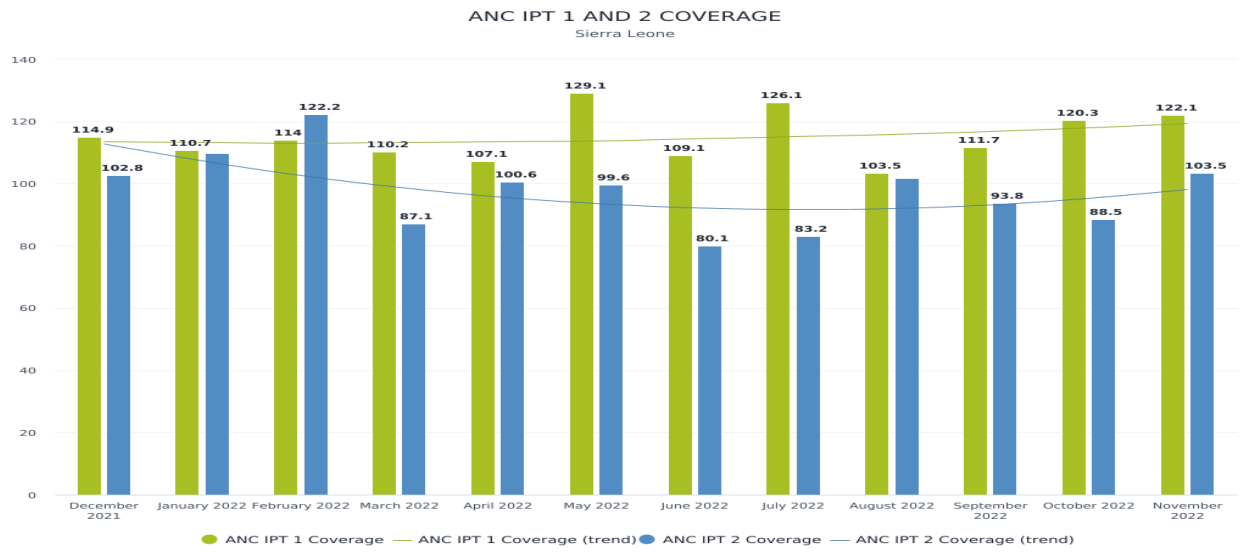


Fig 1: ANC IPT 1 Coverage and ANC IPT 2 Coverage - Sierra Leone

One can use linear regression or polynomial regression to plot the trend line. Linear regression has many disadvantages. It suffers from linear limitation, low-moderate predictive performance, and fear of outliers (Tung, 2020). To have better predictive performance, we used polynomial regression of factor 2 to plot the trend lines of ANC IPT 1 Coverage and ANC IPT 2 Coverage.

The ANC IPT 1 Coverage trend shows a slight upward trend denoting that the vaccination coverage would slightly increase over time. The ANC IPT 2 Coverage trend shows a curve with a minimum during July 2022 and August 2022. This trend shows an increase in vaccination coverage over time.

After exporting the data and using R, we can predict the month when these two trend lines would meet. Plotting the data and applying polynomial regression, we get that the trend lines would meet between April 2023 and May 2023. In other words, ANC IPT Coverage 1 and ANC IPT Coverage 2 would have the same coverage from April to May 2023.

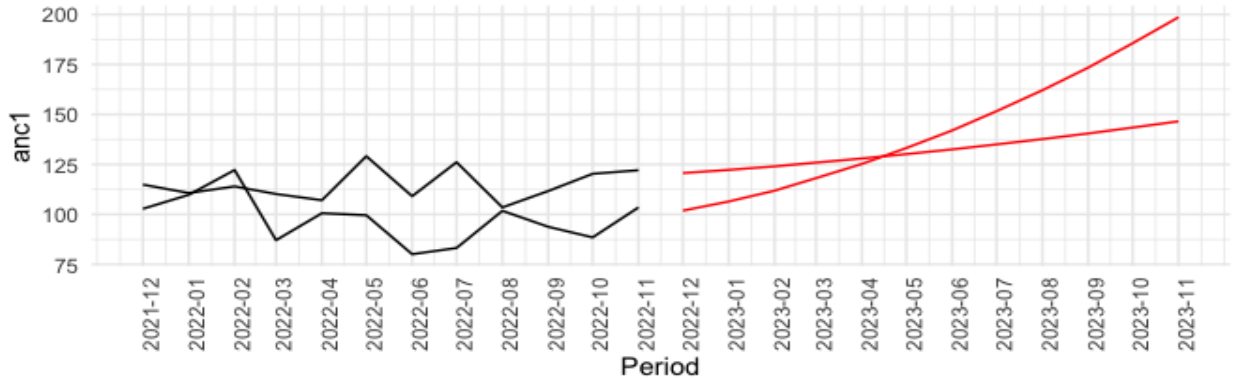


Fig 2: ANC IPT 1 Coverage and ANC IPT 2 Coverage Trend line - Sierra Leone

4. Forecast Coverage:

ANC IPT 2 Coverage for Western Area District from Jan 2021- Dec 2022	
Western Area	
	ANC IPT 2 Coverage
January 2021	119.9
February 2021	293.7
March 2021	154.6
April 2021	99.3
May 2021	117.9
June 2021	69.4
July 2021	75.3
August 2021	216.2
September 2021	107.8
October 2021	157.2
November 2021	74.3
December 2021	138.2
January 2022	119.9
February 2022	293.7
March 2022	99.3
April 2022	154.6
May 2022	117.9
June 2022	69.4
July 2022	75.3
August 2022	216.2
September 2022	107.8
October 2022	74.3
November 2022	157.2
December 2022	138.2

Fig 3: ANC IPT 2 Coverage of Western District (Sierra Leone) from Jan 2021 to Dec 2022

There are many forecasting algorithms to predict the value of a future observation from present or past data. Simple Exponential Smoothing (SES) is one such forecasting algorithm.

DHIS2 has data on ANC IPT 2 Coverage till December 2022. Using the stored data, using SES, we could calculate what would be the forecasted ANC IPT 2 Coverage.

In SES, the equation to forecast requires an alpha value to range between 0 and 1. In this scenario, we are calculating the ANC IPT 2 Coverage of the Western District based on 2021 and 2022 data. As DHIS2 doesn't have any inbuilt SES calculation feature, we export the data in CSV format and use R to forecast. We take two alpha values to compare which is better suited for forecasting/predicting. In the first case, we take the alpha value of 0.1.

Forecast accuracy measures provide critical and conclusive feedback to stakeholders to use a better forecasting model that is associated with the lowest prediction error (Kolade, 2019).

After performing SES and calculating MAPE and MSE, we get a forecasted value of 129.34 with an MSE of 4551.61 and MAPE of 0.41. In the second case, we take the alpha value of 0.8. We get the predicted value of 142.6 with MSE 7753.62 and MAPE of 0.52.

Predicted value of December 2022, ANC IPT 2 Coverage for alpha=0.1 is 129.34

A data.frame: 24 × 5

periodname	ANC.IPT.2.Coverage	forecast	err	squared_error
<chr>	<dbl>	<dbl>	<dbl>	<dbl>
January 2021	119.9	NA	NA	NA
February 2021	293.7	119.90	173.80	30206.4400
March 2021	154.6	137.28	17.32	299.9824
April 2021	99.3	139.01	-39.71	1576.8841
May 2021	117.9	135.04	-17.14	293.7796
June 2021	69.4	133.33	-63.93	4087.0449
July 2021	75.3	126.94	-51.64	2666.6896
August 2021	216.2	121.78	94.42	8915.1364
September 2021	107.8	131.22	-23.42	548.4964
October 2021	157.2	128.88	28.32	802.0224
November 2021	74.3	131.71	-57.41	3295.9081
December 2021	138.2	125.97	12.23	149.5729
January 2022	119.9	127.19	-7.29	53.1441
February 2022	293.7	126.46	167.24	27969.2176
March 2022	99.3	143.18	-43.88	1925.4544
April 2022	154.6	138.79	15.81	249.9561
May 2022	117.9	140.37	-22.47	504.9009
June 2022	69.4	138.12	-68.72	4722.4384
July 2022	75.3	131.25	-55.95	3130.4025
August 2022	216.2	125.66	90.54	8197.4916
September 2022	107.8	134.71	-26.91	724.1481
October 2022	74.3	132.02	-57.72	3331.5984
November 2022	157.2	126.25	30.95	957.9025
December 2022	138.2	129.34	8.86	78.4996

Mean Squared Error is 4551.614
Mean Absolute Percentage Error is 0.4067736

(a)

Predicted value of December 2022, ANC IPT 2 Coverage for alpha=0.8 is 142.6

A data.frame: 24 × 5

periodname	ANC.IPT.2.Coverage	forecast	err	squared_error
<chr>	<dbl>	<dbl>	<dbl>	<dbl>
January 2021	119.9	NA	NA	NA
February 2021	293.7	119.90	173.80	30206.4400
March 2021	154.6	258.94	-104.34	10886.8356
April 2021	99.3	175.47	-76.17	5801.8689
May 2021	117.9	114.53	3.37	11.3569
June 2021	69.4	117.23	-47.83	2287.7089
July 2021	75.3	78.97	-3.67	13.4689
August 2021	216.2	76.03	140.17	19647.6289
September 2021	107.8	188.17	-80.37	6459.3369
October 2021	157.2	123.87	33.33	1110.8889
November 2021	74.3	150.53	-76.23	5811.0129
December 2021	138.2	89.55	48.65	2366.8225
January 2022	119.9	128.47	-8.57	73.4449
February 2022	293.7	121.61	172.09	29614.9681
March 2022	99.3	259.28	-159.98	25593.6004
April 2022	154.6	131.30	23.30	542.8900
May 2022	117.9	149.94	-32.04	1026.5616
June 2022	69.4	124.31	-54.91	3015.1081
July 2022	75.3	80.38	-5.08	25.8064
August 2022	216.2	76.32	139.88	19566.4144
September 2022	107.8	188.22	-80.42	6467.3764
October 2022	74.3	123.88	-49.58	2458.1764
November 2022	157.2	84.22	72.98	5326.0804
December 2022	138.2	142.60	-4.40	19.3600

Mean Squared Error is 7753.615
Mean Absolute Percentage Error is 0.5169641

(b)

Fig 4: Forecasted ANC IPT 2 Coverage of Western District (Sierra Leone) from Jan 2021 to Dec 2022

Though the predicted value of alpha = 0.8 is close to the observed value, the MAPE and MSE are lower for alpha = 0.1. This observation is because there is an enormous variety of coverage values between two consecutive months. A lower alpha value tends to slowly change w.r.t. data, whereas a higher alpha value tends to match the variation of the data. Hence, instead of going with the error or closeness of the forecasted value to the actual value, we must analyze it with a multi-line plot. Here, the black line represents the actual coverage values, whereas the red and blue lines represent forecasted values with alpha = 0.1 and alpha = 0.8, respectively. Here we can see that the line alpha = 0.8 (blue) tries to follow the data deviations, whereas alpha = 0.1 does not.

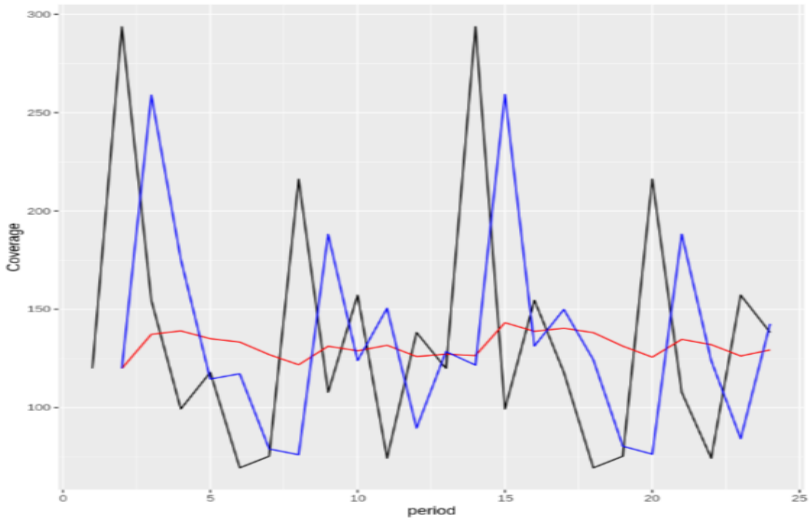


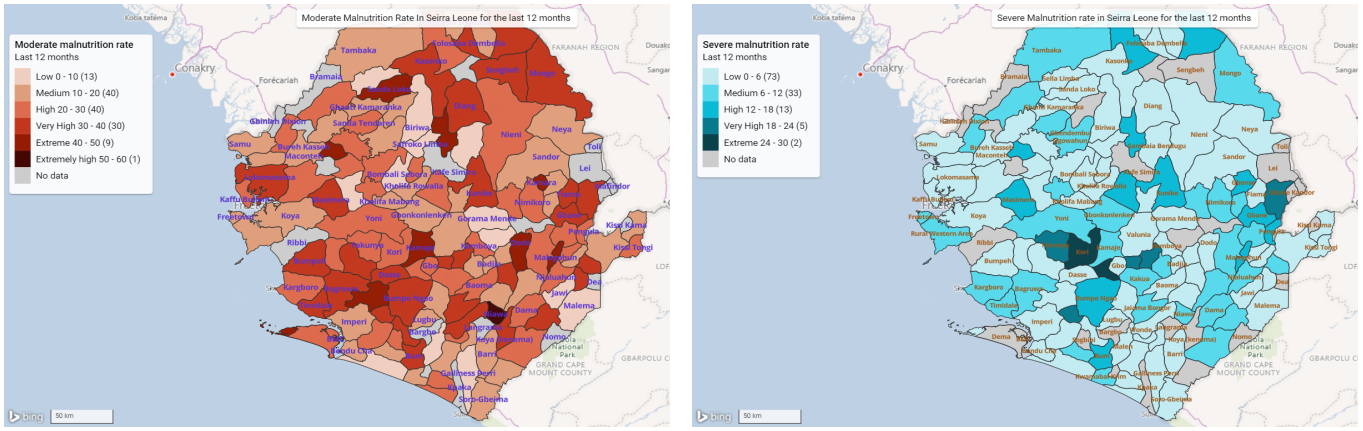
Fig 5: Multi-line plot of Actual and Forecasted ANC IPT 2 Coverage
Western District (Sierra Leone) Jan 2021 - Dec 2022

5. Malnutrition in Sierra Leone:

Malnutrition is prevalent throughout Sierra Leone (UNICEF, 2022). According to UNICEF, 33% of children under five years suffer from acute malnutrition annually (UNICEF, 2022). Malnutrition in children causes wasting (low weight compared to height), stunting (shorter height compared to age), or being overweight or obese (Abbott Nutrition News, 2021). Malnutrition can affect a child's cognitive capability, future work opportunities, and finances (Abbott Nutrition News, 2021).

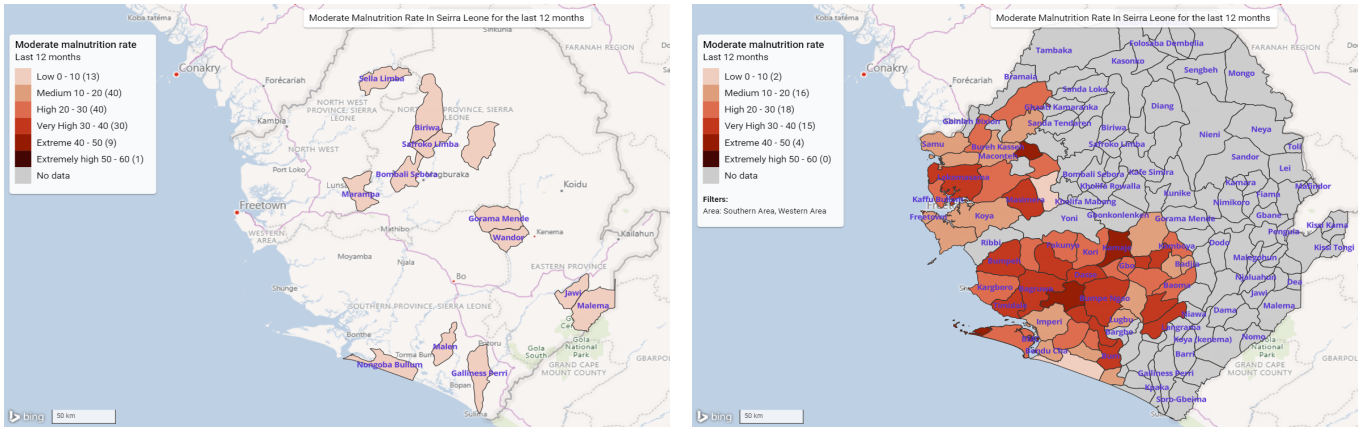
Sierra Leone has close to 150 chiefdoms. The DHIS2 contains Moderate and Severe malnutrition data throughout Sierra Leone. Fig 6 shows the choropleth map of (a) moderate malnutrition rate and (b) severe malnutrition rate by Chiefdoms for the past 12 months. We employed a custom legend with six classes (Low, Medium, High, Very High, Extreme, Extreme High) of interval 10 for Moderate malnutrition rate and five classes (Low, Medium, High, Very High, Extreme) of interval 6 for Severe malnutrition rates using DHIS2 tool.

Malema chiefdom of Kailahun district had the lowest Moderate Malnutrition Rate of 2.2 in Sierra Leone. This chiefdom is in the southeast part of the country. Some of the chiefdoms in Sierra Leone that have a high Moderate malnutrition rate and are close to Freetown (the capital city) are Dibia (43.1%), Masimera (34%), Bumpeh (32.3%), Kaffu Bullom (27%), Lokomasama (31.7%), Kongbora (27.4%), Magbema (24.8%), Buya Romende (21%), Maforki (22%), Yoni (23.3%), Fakunya (29.9%), Kaiyamba (30.7%), Bagruwa (31.5%), Timidale (37.8%), Kargboro (22.6%) and Dema (40.1%). Dibia has had the highest Moderate Malnutrition Rate compared to the rest in the above list.



(a) Moderate Malnutrition Rate (b) Severe Malnutrition Rate

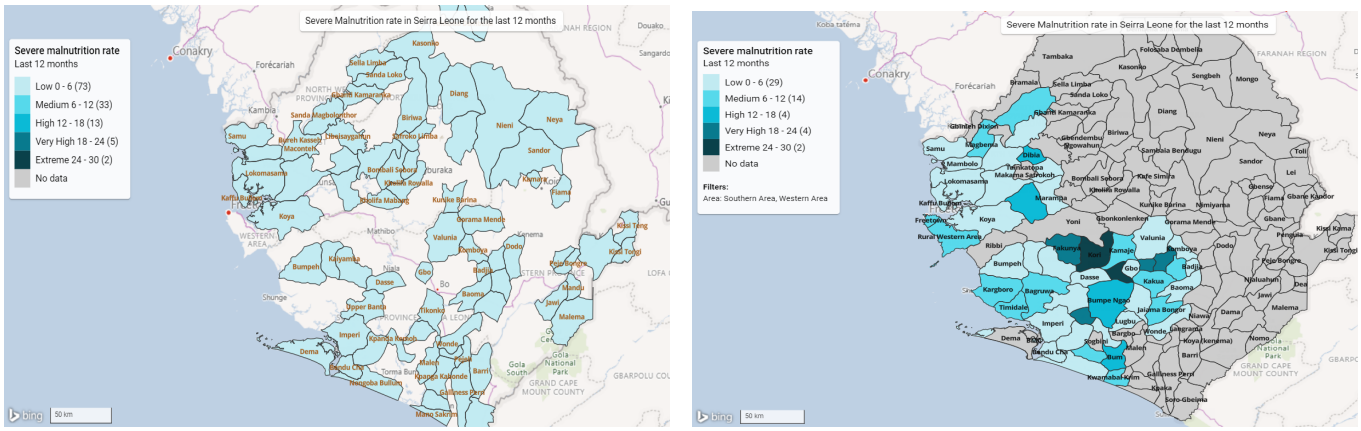
Fig 6: Last 12 months Malnutrition Rate in Sierra Leone by Districts



(a) Moderate Malnutrition Rate - Low (b) Moderate Malnutrition Rate - near Freetown (Capital City)

Fig 7: Moderate Malnutrition Rate in Sierra Leone in the last 12 months by Districts

Biriwa chiefdom of Bombali district has had the lowest severe malnutrition rate of 0.11 in Sierra Leone. This chiefdom is in the North Central part of the country. Some of the chiefdoms that have high Severe Malnutrition Rates and are close to the capital city of Freetown are Masimera (13.5%), Fakunya (19%), Kori (24.3%), Bumpe Ngao (16.1%), and Lower Banta (18.8%). Kori has had the highest Severe malnutrition rate in the above list for the past 12 months.



(a) Severe Malnutrition Rate - Low (b) Severe Malnutrition Rate - near Freetown (Capital City)

Fig 8: Severe Malnutrition Rate in Sierra Leone in the last 12 months by Districts

From fig 6(a), it is evident that many chiefdoms suffer from Moderate Malnutrition. Only a few (around 13) chiefdoms had a Low Moderate Malnutrition Rate in Sierra Leone. Most of them are present in central and south Sierra Leone. From 6(b), we can conclude that only a few chiefdoms have recorded high to extremely severe malnutrition rates in Sierra Leone. Most of the chiefdoms with High to Extreme Severe Malnutrition Rates are present in Central Sierra Leone. Also, we can conclude that proximity to the capital city does not ensure a low malnutrition rate.

The other way to represent the above maps (fig 6 - fig 8) is by using bubble maps which would define the malnutrition rate based on the size of the bubble. But choropleth has better visual appeal since bubble map w.r.t. Chiefdoms of Sierra Leone would result in close to 150 bubbles in the map, which would be difficult to analyze visually which malnutrition rate class a particular district belongs to.

6. Computer Vision and AI to predict malnutrition rate

With the advancement of technology and methods, one can use scientific knowledge and tools to find answers to any questions. That is true even for predicting or forecasting health data. For example, we predicted Bo districts' Severe Malnutrition Rate class using other districts' data and CNN with ResNet architecture and ImageNet weights. CNN enables the extraction of features on the overall spatial dimensionality of the signal (Fraiwan et al., 2022). It is modeled as a feed-forward network with transnational and rotational invariance to analyze visual imagery (Fraiwan et al., 2022). The depth of the model is 6, which contains a Convolution Base, 2d Convolution, 2d Max Pooling, flattened, Dense, and Output layers.

For training, we collected images of the choropleth map of Sierra Leone depicting the monthly severe malnutrition rate by the district for the years 2021 and 2022. We obtained 21 choropleth map snapshots (no data for Oct 2022 and Nov 2022). We also made A CSV file consisting of information on the image path and corresponding Bo's Severe Malnutrition Rate class.

These images were loaded, split into training and testing, and trained in R. The model achieved a training accuracy of 0.9 and a loss of 0.48. The model predicted 3/5 test images correctly.

The inaccuracies and drawbacks of the model are due to the small dataset. Since the data set was small and Bo district only had Low and Moderate Severe Malnutrition Rate classes in 2021 and 2022, the model did not perform accurately. Also, this model could not be used to predict other types like High, Very High, and Extremely Severe Malnutrition Rates since the dataset does not contain those scenarios.

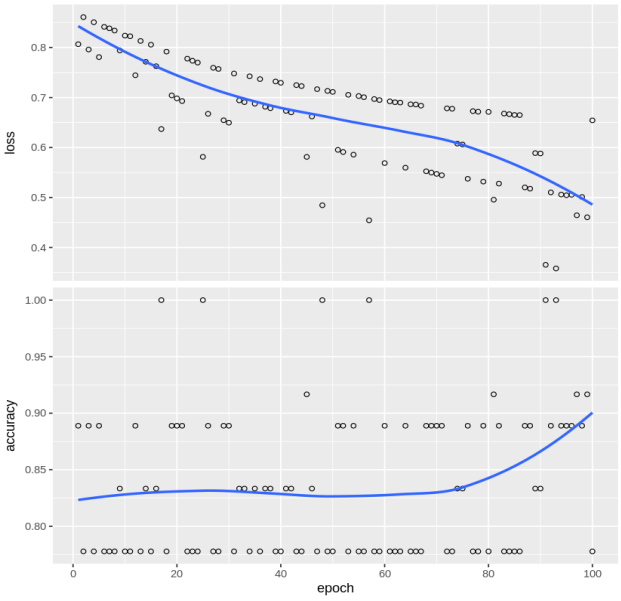


Fig 9: Training Loss and Accuracy of ResNet model

7. Measles Coverage in Sierra Leone

Measles is a serious virus-borne disease that is highly contagious but preventable by a vaccine (World Health Organization, 2018). Children are most vulnerable to measles and its complications (World Health Organization, 2019). When children are not immunized, the virus can quickly spread and cause severe illness, impairment, and death (World Health Organization, 2018).

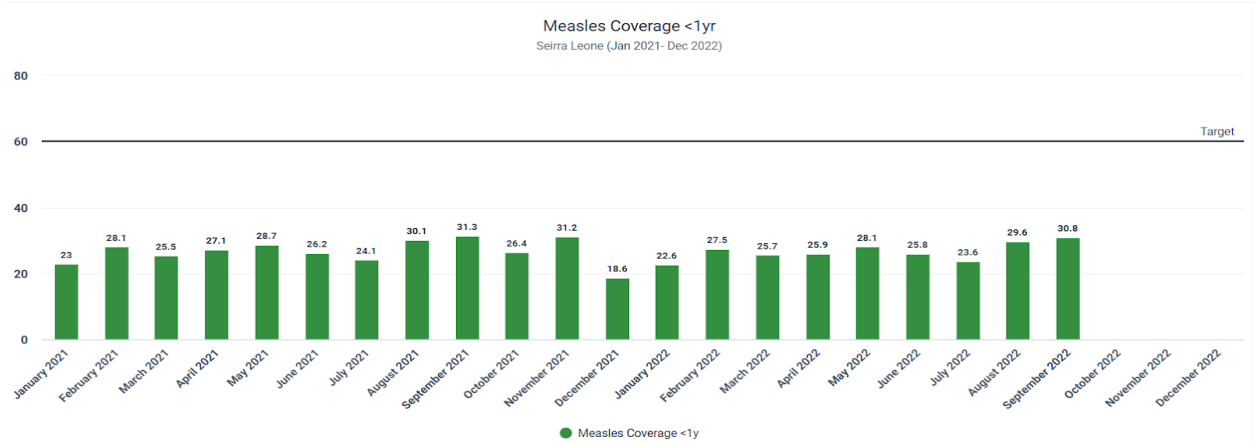


Fig 10(a) Measles Coverage <1y in Sierra Leone by months, Target = 60%

DHIS2 contains measles coverage data for children less than one year of age. When plotted and analyzed per month (Fig 10(a)), we can observe that in none of the months in the last 12 months, the country reached the target of 60% measles vaccine coverage. As the coverage ranges between 18 to 32, we can check which months did not meet the halfway mark (median) of the range (i.e., 25).

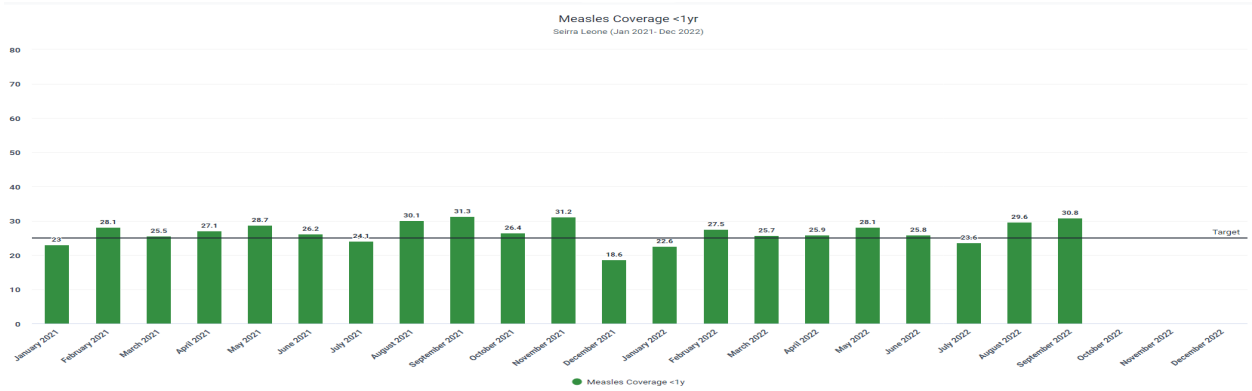


Fig 10(b) Measles Coverage <1y in Sierra Leone by months, Target = 25%

From the given plot (Fig 10 (b)), the months January 2021 (23%), July 2021 (24.1%), December 2021 (18.6%), January 2022 (22.6%), and July 2022 (23.6%) didn't cross coverage of 25%.

Fig 11 shows the plot of the measles coverage <1y in Sierra Leone by districts with a target of 25%. Except for the Western Area district (53.3%), all other districts didn't reach the target. Bo (24,6%), Kenema (23.6%), and Moyamba (23.3%) are close to the target but didn't meet the new target calculated above. The other districts which didn't meet the target are Bombali (17.2%), Bonthe (14.6%), Kailahun (20.8%), Kambia (10.9%), Koinadugu (11.7%), Kono (9.7%), Port Loko (13.5%), Pujehun (20.8%) and Tonkolili (12.7%).

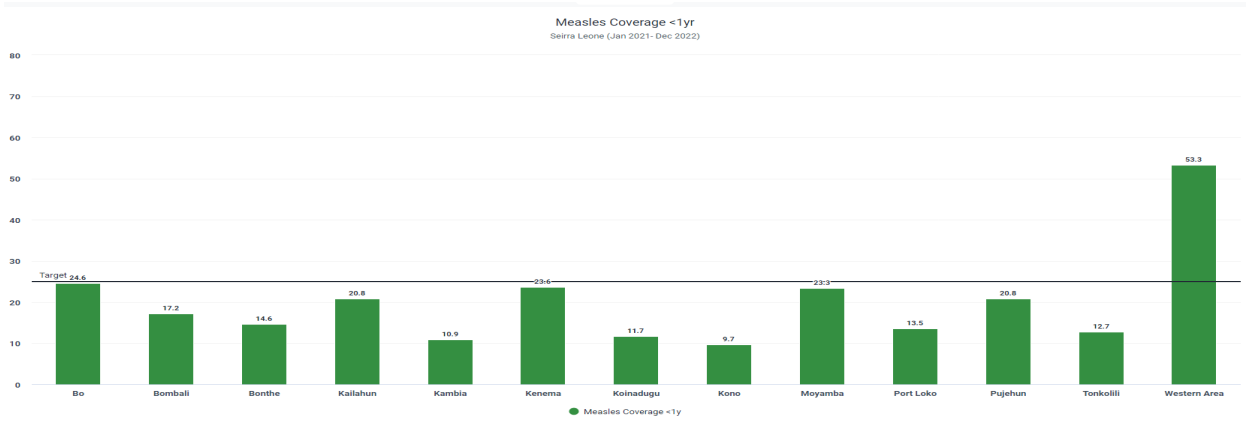
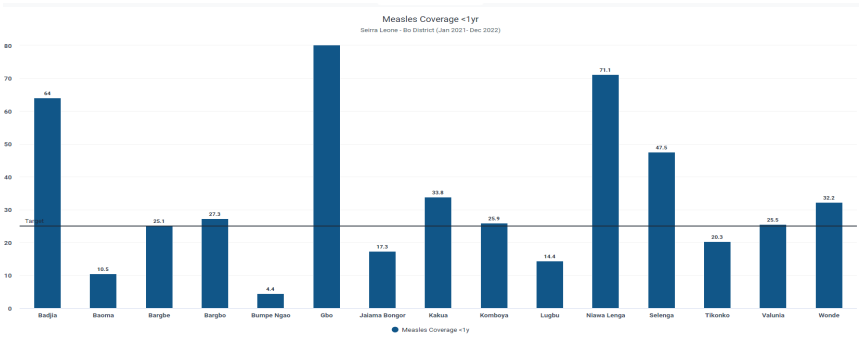
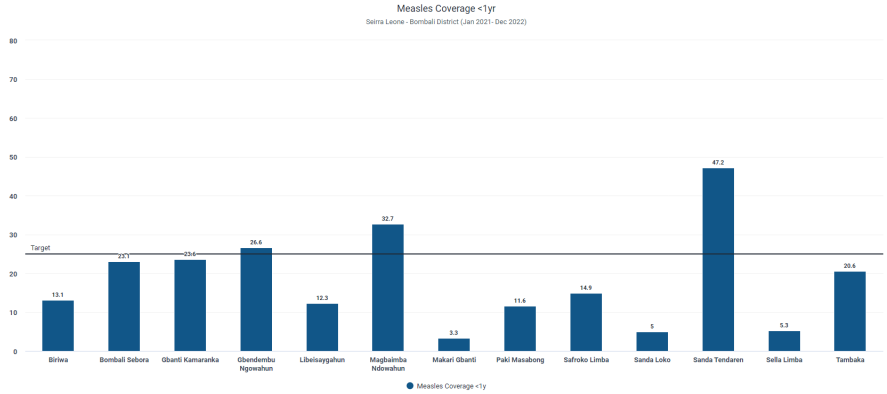


Fig 11: Measles Coverage <1y in Sierra Leone by Districts, Target = 25%

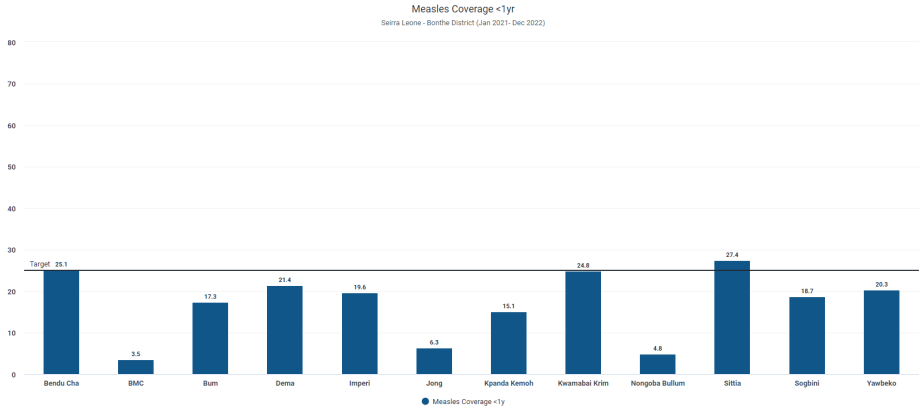
On further drilling down to chiefdoms, we get Fig 12 (a-h). A bar plot is an apt representation of this type of data. But since there are around 150 chiefdoms, it is better to plot 1-2 district chiefdoms at a time. By analyzing the below graphs, almost 30% of the chiefdoms have met the target of 25% with Gbo, the chiefdom of Bo District has the highest coverage (102.1%).



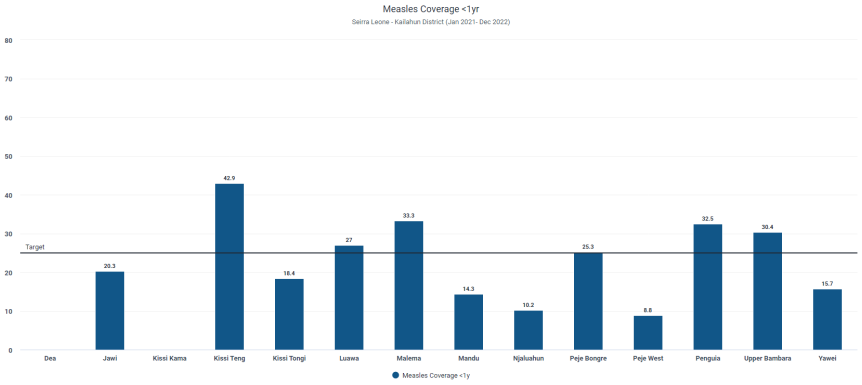
(a) Bo District (Jan 2021- Dec 2022)



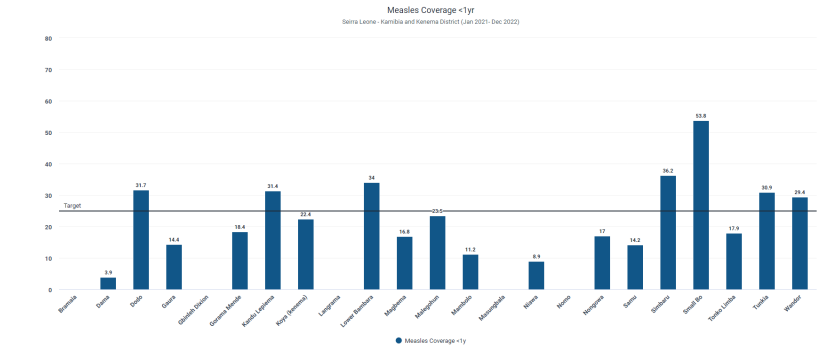
(b) Bombali District



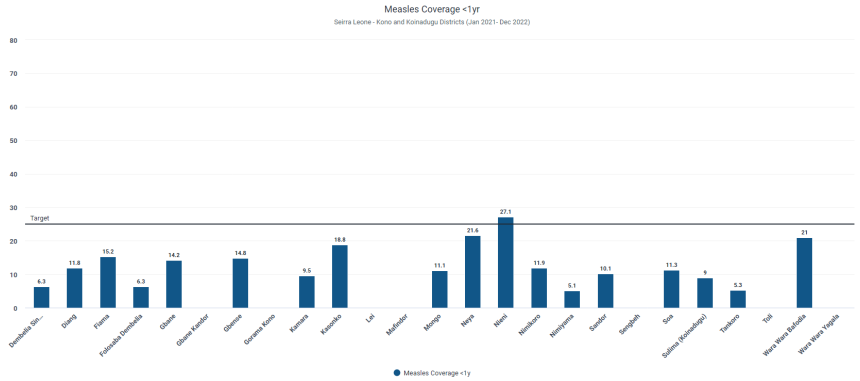
(c) Bonthe District



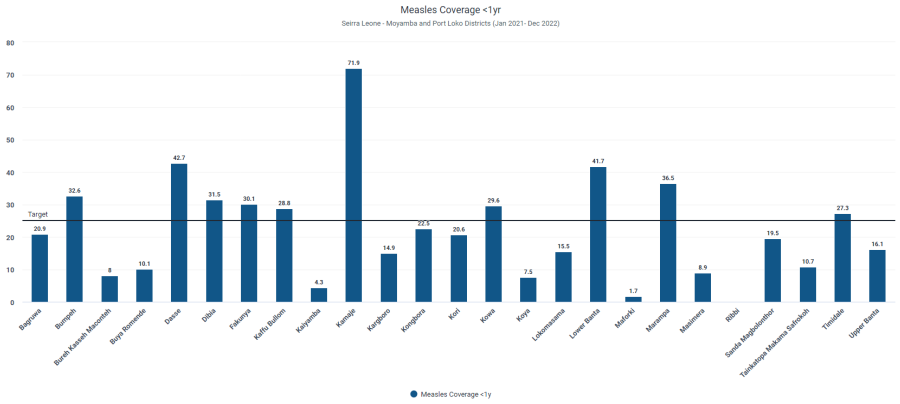
(d) Kailahun District



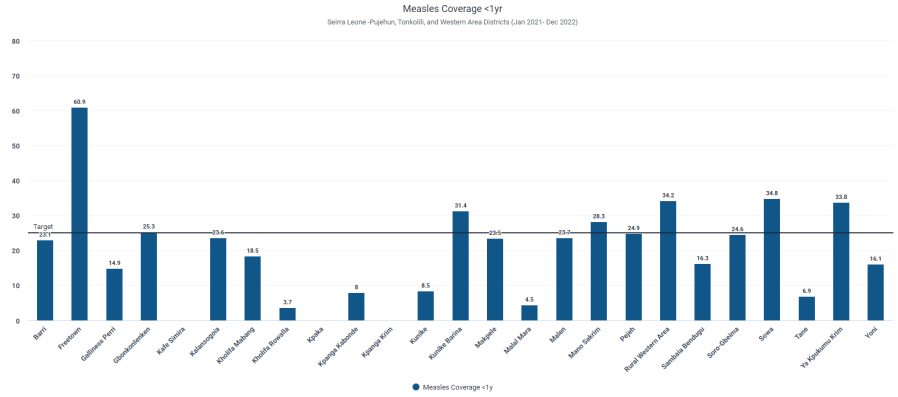
(e) Kambia and Kenema Districts



(f) Koinadugu and Kono Districts



(g) Moyamba and Port Loko Districts



(h) Pujehun, Tonkolili and Western Area Districts

Fig 12: Sierra Leone Measles Coverage <1y by Chiefdoms (Jan 2021 - Dec 2022)

On further analyzing Sierra Leone Measles vaccination coverage <1y old based on facilities, we get the plot shown in Fig 13. The data is segregated based on facility type and ownership. There are five facility types (CHC, CHP, Clinic, Hospital, and MCHP). Each facility type has four facility ownerships (Mission, NGO, Private Clinic, and Public Facilities). Most of the facility types don't have facility ownership data. In the ones where data exists, all facilities have met the target. Also, it is interesting to note that in CHC, coverage by NGOs and Private clinics is greater than coverage by Public facilities.

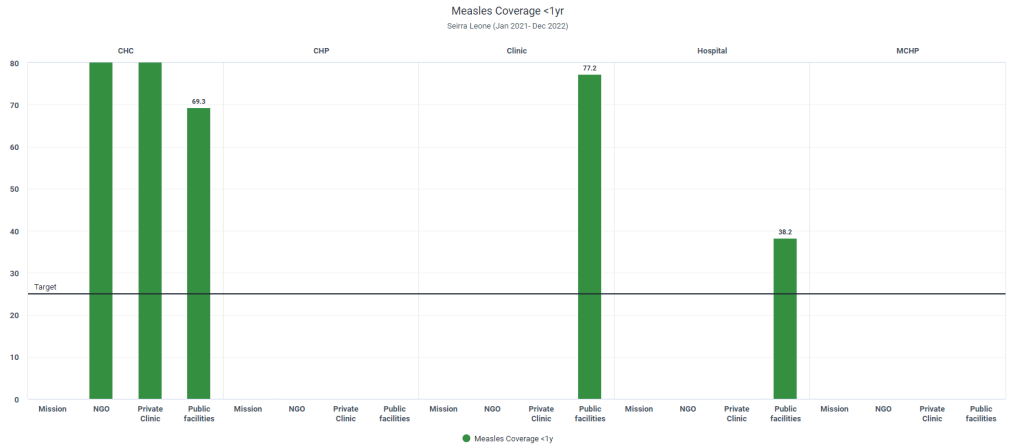


Fig 13: Sierra Leone Measles Coverage <1y by Facilities (Jan 2021 - Dec 2022)

The measles coverage over time shows a slight upward trend that signifies the vaccine coverage will increase with time. To denote the progress over time, either bar chart, line chart, or scatter plots are most applicable. Since many visualizations in the project have a bar chart and scatter plot charts are more appealing when there is a large set of data points, the line chart is the best visualizer in this scenario.

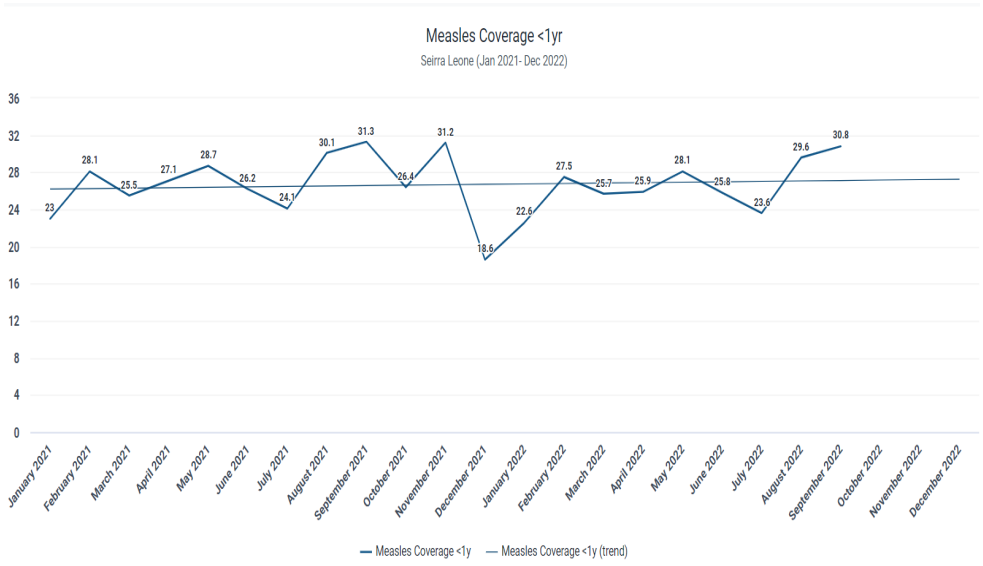


Fig 14: Sierra Leone Measles Coverage <1y over time (Jan 2021 - Dec 2022)

8. Measles Coverage - Dropout rate

Dropout occurs when the patient receives the 1st dose but hasn't come back for the second. This rate is calculated by comparing the number of infants who start the immunization and the number of infants who complete it (OpenLearn Create, n.d.). Here, we refer to the dropout rate between receiving the first dose of pentavalent vaccine (Penta1) and receiving a single dose of measles vaccine (OpenLearn Create, n.d.).

If there is a significant dropout rate between Penta1 and the measles vaccination, it may indicate that parents have trouble using health services in general (OpenLearn Create, n.d.). A health post with a dropout rate of more than 10% has a service utilization issue, meaning that many people are not using the available services (OpenLearn Create, n.d.).

DHIS2 contains Measles vaccination coverage data and dropout rates. From fig 15, we can interpret that Penta 1 dropout rates are high, and the corresponding measles vaccination coverage is low. But over time, the dropout rate decreased and measles coverage increased. This is evident with the trend lines. It shows that initially there was a lack of utilizing services, however with time, patients tend to stick to the vaccination appointments.

To prove the relation between dropout rate and measles coverage, we can use a correlation between the two. Since DHIS2 doesn't have a correlation feature, we export the data to R in CSV format. We use Pearson correlation since we can see linear relationships based on the trendlines and this type of correlation works best for raw data instead of rank-ordered variables. On using Pearson correlation between the 2 and plotting (fig 16), we get that the correlation value is -0.68, and as the dropout rate increases, the measles coverage decreases. This shows that both variables have an inverse relationship.

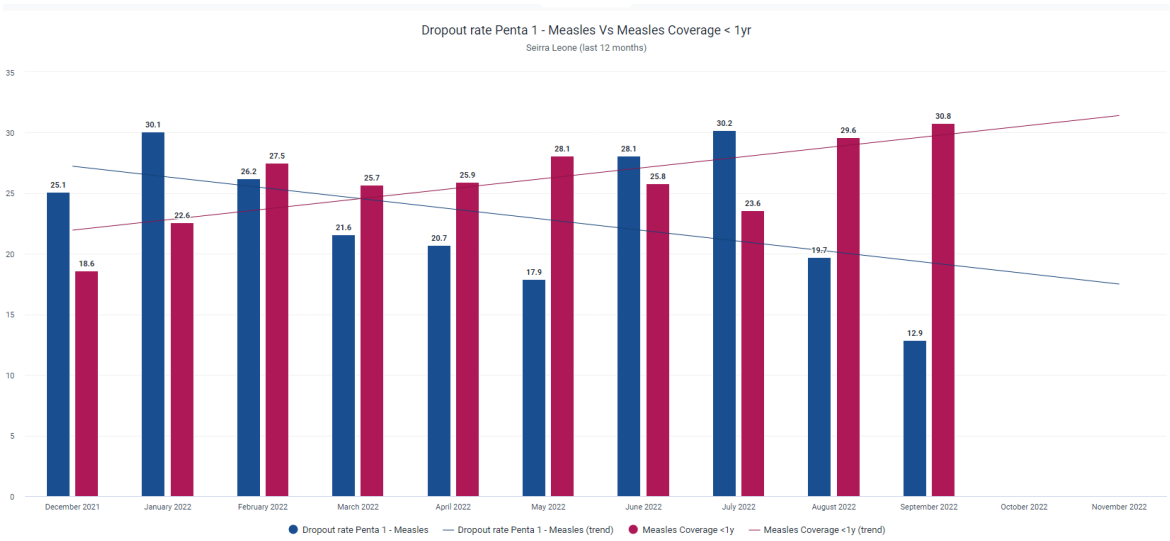


Fig 15: Dropout rate Penta 1 Measles vs Measles coverage - Sierra Leone (Last 12 Months)

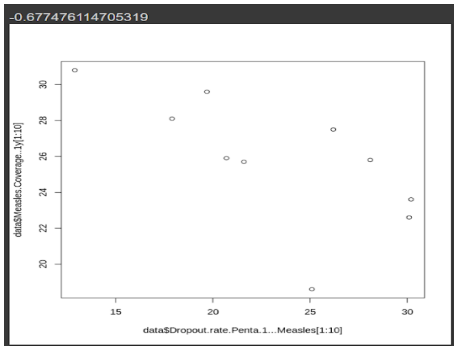


Fig 16: Correlation plot - Dropout rate Penta 1 Measles vs Measles coverage - Sierra Leone (Last 12 Months)

9. Births by skilled attendants:

Skilled birth attendance (SBA) is an important strategy for reducing the maternal mortality ratio (MMR) (Ameyaw & Dickson, 2020). In countries with low SBA, the lifetime risk of maternal death is high (Ameyaw & Dickson, 2020). The presence of a skilled birth attendant can reduce the risk of death due to intrapartum-related complications or stillbirth by 20% (Ameyaw & Dickson, 2020). DHIS2 consists of births by skilled attendants. Using the data for the past 12 months by districts, we plot the symbol proportional map (Fig 17). We classify the birth by skilled attendants into three categories - low, medium and high. From the below map (Fig 17), we can observe that Loko (50%) and Kambia (53.7%) have the lowest births by skilled attendants. It is interesting to note that these districts are close to the capital city. This low percentage signifies that there are not enough skilled health workers based on the number of patients.

The other way to plot this data could be using bar plot, choropleth map, and a single color buble map. But the below Symbol Proportional map shows the districts which have low births by skilled attendants (color) and also which have the lowest (size).

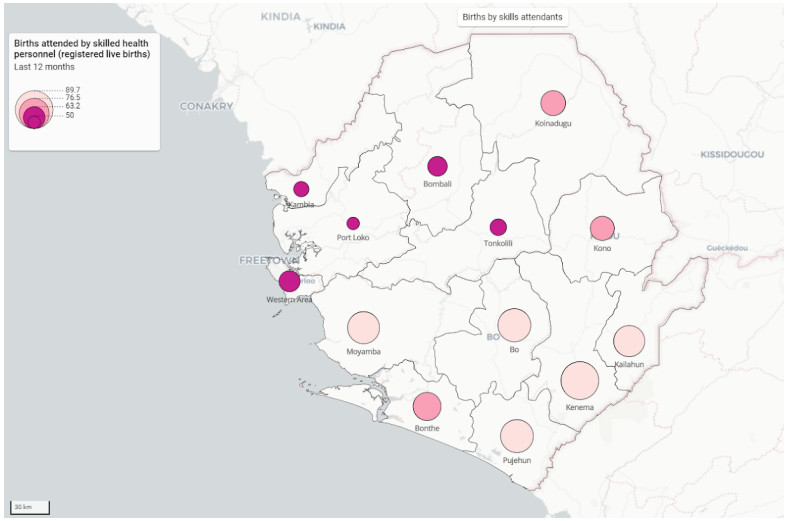


Fig 17: Symbol Proportional Map - Sierra Leone: Births by Skilled Attendants

10. Dashboard:

Dashboard shows a visual summary of the analysis which captivates and imprints information to the audience's mind. Below (Fig 18) is the summarized dashboard of the project which answers many health questions related to Sierra Leone's malaria vaccinations, malnutrition rate, measles and births by skilled attendants.

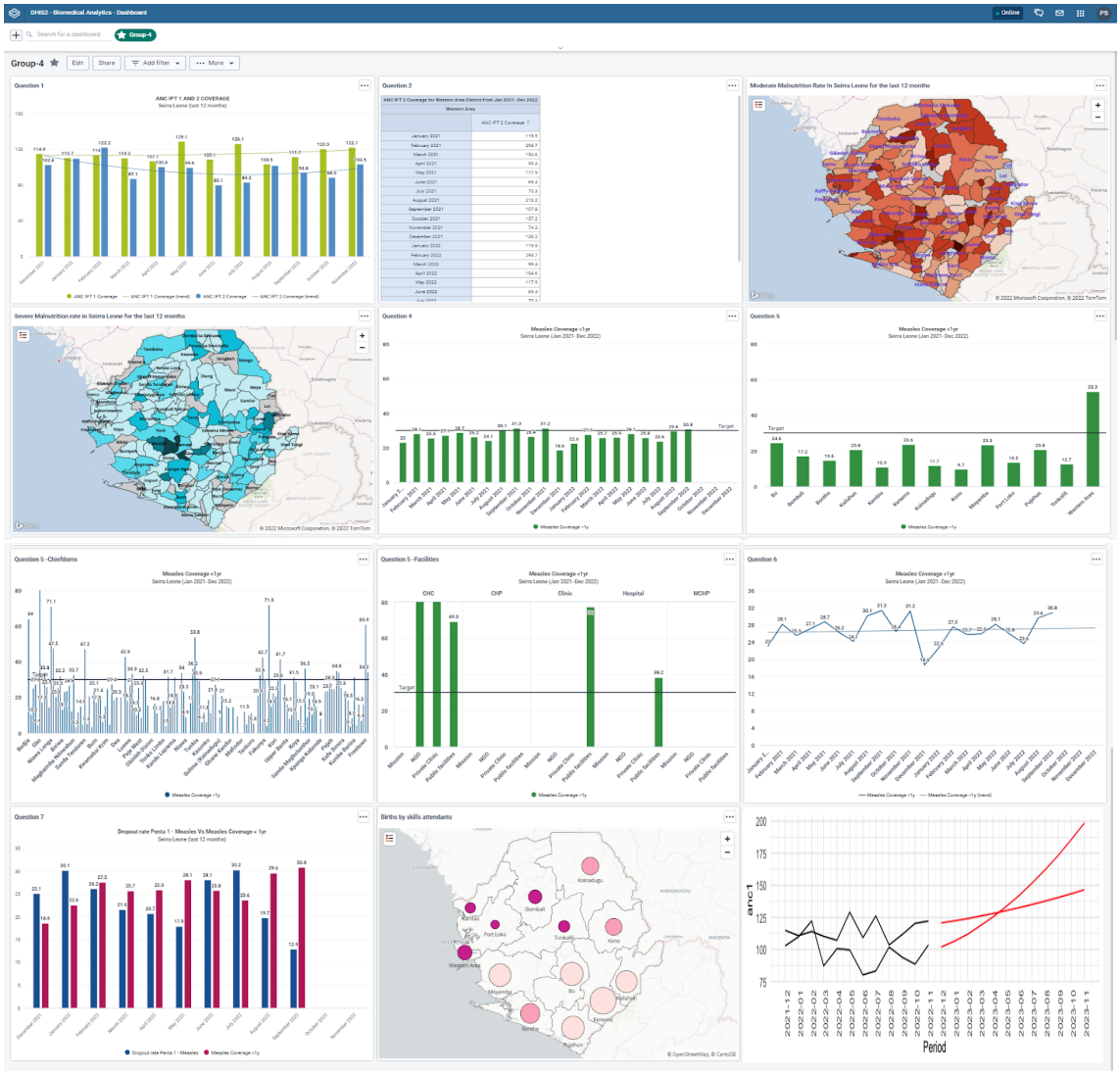


Fig 18: Analysis Dashboard - Sierra Leone

11. Validations and Quality issues

There are few validation rules which must be taken into account for future analysis. First, the number of measles doses given must be greater than the total affected population. This would ensure that vaccines are not only given to affected ones but also to people who did not yet get into contact with the disease and would enable the health system to go into proactive preventive treatment. Second, the total percentage of ANC IPT 1 Coverage must be always greater than or equal to the total ANC IPT 2 Coverage, since only after the first dose, the health worker can administer the 2nd dose. Third, the total number of deaths caused by malnutrition must be

smaller than or equal to the total number of malnutrition cases detected. This enables tracking of all the cases.

Some of the data in DHIS2 suffered from data completeness. This malnutrition dataset had data missing from October 2022 to December 2022.

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